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

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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 imply the research of visually observable patterns viewed on the plant. Health monitoring and ailment detection on plant is very imperative for sustainable agriculture. It is very hard to screen the plant illnesses manually. It requires first- rate quantity of work, expertize in the plant diseases, and additionally require the immoderate processing time. Hence, image processing is used for the detection of plant diseases. Plant Disease Identification includes the steps like 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, then 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 type of costly equipment.*

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

INTRODUCTION

Modern applied sciences have given human society the capability to produce sufficient meals to meet the demand of greater than 7 billion people. However, meals safety stays threatened by way of a quantity of elements which include local weather change. Plant illnesses are no longer solely a hazard to meals protection at the world scale, however can additionally have disastrous penalties for smallholder farmers whose livelihoods rely on wholesome crops. In the growing world, extra than eighty percentage 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 huge utility of pesticides have in the previous decade increasingly more been supplemented by way of built-in pest administration (IPM) approaches. Identifying an ailment successfully when it first seems is an integral step for environment friendly disorder management. Historically, disorder identification has been supported by using agricultural extension agencies or different institutions, such as neighborhood plant clinics. In greater current times, such efforts have moreover been supported by way of presenting records for ailment analysis online, leveraging the growing Internet penetration worldwide. Even extra recently, equipment primarily based on cellular

Telephones have proliferated, taking benefit of 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 discover ailments due to the fact of their computing power, high- resolution displays, and massive built-in units of accessories, such as superior HD cameras. It is broadly estimated that there will be between 5 and 6 billion smartphones on the globe by way of 2020. At the cease of 2015,already 69% of the world's populace had get entry to cell broadband coverage, and cell broadband penetration reached 47% in 2015. 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 computerized photograph recognition, if technically feasible, can be made on hand at an unheard of scale. Here, we show the technical feasibility the use of a deep gaining knowledge of method utilizing 54,306 pictures of 14 crop species with 26 illnesses (or healthy) made overtly accessible via the assignment Plant Village[3].Deep neural networks have these days been correctly utilized in many various domains as examples of stop to stop learning. Neural networks furnish a mapping between an input—such as an photo of a diseased plant—to an 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 certainly mapping the enter layer to the output layer over a sequence of stacked layers of nodes. The project is to create a deep community in such a way that each the shape of the community as properly as the features (nodes) and aspect weights efficiently map the enter to the output. Deep neural networks are skilled by way of tuning the community parameters in such a way that the mapping improves at some point of the coaching process. This technique is computationally difficult and has in latest instances been accelerated dramatically via a wide variety of each conceptual and engineering breakthroughs.

To address the issues caused by limited access to specialists, especially in developing countries, there has been considerable research focusing 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 we focal point on strategies that can assist us higher apprehend the educated fashions in order to keep away from the black field impact and to make certain the reliability of the acquired results.

The system can help for practicing 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 disease

RELATED WORK

In this research paper, they propose 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. They also show that this accuracy is reached by increasing the depth of the model. Finally, by analyzing the resulting models with a simple visualization technique, they are able to 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 LifeCLEF 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 by 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 data set and the Swedish leaf data set. They want to compare a traditional method and a method consider 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].

In this research paper, they have 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 utilized. It is found that venations of different orders have been chosen to uniquely represent each of the plant species. From the experimental results, they justified that learning the features through CNN can provide better feature representation for leaf images compared to hand-crafted 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 recognize 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 is able to classify the selected Ficus species with acceptable accuracy[5]

Deep Learning for plant identification using vein morphological patterns, here they propose 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. They also show that this accuracy is reached by increasing the depth of the model. Finally, by analyzing the resulting models with a simple visualization technique, they are able to discover which vein patterns are relevant[6].

In this research paper they haveapproach which can help to control growth of diseases on Plants using the pesticides in the quantity needed so that excess use of pesticides can be avoided. Automatic identification of plant diseases is an important task as it may be proved beneficial for farmer to monitor large field of plants, and identify the disease using machine learning approach[7].

In this research paper, they have proposed work is 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 color 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 in order to take preventive measures to maximize the yield[8].

In this paper, they propose to use the concept of plant electrome to automatically identify whether different environmental cues cause specific changes in the electrical signals of soybean plants. In order to verify such hypothesis, they considered using machine learning algorithms and arithmetic interval, 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 to collect a huge amount of data about thousands of species. So it will most likely require collaborative efforts of analysts in this field interested in 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 analyzing the resulting models with a simple visualization technique [10].

As the 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 popularization, and so on improving the performance of mobile-based plant identification models attracts increased attention from scholars[11].

In order to test this hypothesis, quantifications of a variety of 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 the development and physiological responses of plants 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, are also emerging 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 through modeling of 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 and demonstrates that our ability to predict future diversity 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 utilization before launch are specific to choice, while variables for launch experience and utilization after launch are specific to outcomes [15].

METHODOLOGY

Images from herbarium specimens of three Ficus species: F. benjamina, F. pellucidopunctata and F. sumatrana, were taken from University of Malaya Herbarium (acronym KLU), situated in the Rimba Ilmu Botanic Garden. A total of 54 sheets of herbar-ium specimens (F. benjamina, 21; F. pellucidopunctata, his section presents a survey on approaches used in reference research papers taken into consideration. The given table analyzes and illustrates all major 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, with the exception of few F. benjam-ina specimens, which were collected from Kluang,Johor. The specimens were collected between the years 1961 and 2010, with most specimens being col-lected in 1986. All specimens have been identified and had annotation tags on the herbarium 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 Win-dows 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, syconiums and others. Where possible, only intact leaves were selected that had no apparent tearing and also free of dam-age from pest or disease. Young leaves that are evi-dently small sized were ignored. Selected leaves were cropped out and saved as new images with a stan-dard resolution (1800 × 1800 pixel). 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 totaling to 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 huge con-trast with the background, confusing the algorithms to draw the boundary based on shadow instead of on the leaf. Thus, it should be removed before image seg-mentation. Firstly, the image RGB value was changed to HSV value. Then, the channel with the most clear contrast between object and shadow was selected and used to identify the object boundary. As HSV value conversion alters the original color, this step serves as a 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 trans-formed into a set of parameters that describe the leaf features. There are four classes of features extracted in this study: morphological features (shape), Hu moment invariants feature, texture features and his-togram of oriented gradients. These features were selected specifically to obtain the important properties for image leaves, and to obtain 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 diseases is one of the most common disease and can be caused by many reasons like fungal infection, bacteria, allergy, or viruses, etc. In general, plant diseases are chronic, infectious and sometimes may develop to damage plant which would lead to unpleasant circumstances. Therefore it is very important that the plant disease is detected at a very early stage. The deep learning algorithms have a huge potential in the real world plant disease identification.. The authors are focused on to automate the process of plant disease identification and classification can be very helpful and takes less time for identified as well. A number of irrelevant variables can be reduced through image filtering, image rotation, and Euclidean distance transformation applied in image pre-processing. Image Processing with SVM classifier and CNN classifier. According to the result obtained, 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 there related to the provide picture by the user and also some suggestion about the diseases that how it will be cure. It will help in agriculture sector. This will help farmer to get idea about the plants diseases so they can take proper measurement to grow plants. Our system's main objective is to work for social cause.

REFERENCES

1. Guillermo L. Grinblat , Lucas C. Uzal , M onica G. Larese and Pablo M.Granitto,French Argentine International Center for Information and Systems Sciences,UNR- CONICET, Argentina May 27, 2016.
2. Mostafa Mehdipour Ghazia, Berrin Yanikoglua,Erchan Aptoulab,Faculty of engineering and Natural Sciences, Sabanci University, Istanbul,TurkeyInstitute of Information Technologies,GebzeTechnica University,Kocaeli, Turkey 2017
3. Truong Quoc Bao, Nguyen Thanh Tan Kiet, Truong Quoc Dinh & Huynh Xuan Hiep,Journal of Information and Telecommunication(2020),
4. Sue Han Lee, Chee Seng Chan,Paul Wilkin, Paolo Remagnino,University of Malaya, Kingston University, United Kingdom 2015
5. Soon Jye Kho, Sugumaran Manickam, Sorayya Malek, Mogeeb Mosleh & Surinder Kaur Dhillon,Frontiers in Life Science (2018)
6. D.V. Nazarenko, P.V. Kharyuk,I.V. Oseledets, I.A. Rodin,O.A Shpiguna,Moscow, Russia, 8 June 2016
7. Jyoti Shirahatti, Rutuja Patil, Pooja Akulwar,International on Communication and Electronics Systems (ICCES 2018)
8. Danillo Roberto Pereira, João Paulo Papa, Gustavo Francisco Rosalin Saraiva,GustavoMaia Souza,Universidade do Oeste Paulista, Presidente Prudente, SãoPaulo, Brazil, 2018
9. C.Amuthalingeswaran, S.Alexpandi,J.Elamathi, Dr. P.Renuga, S.Santhana Hari, Mr. M Sivakumar,Proceedings of the Third International on Trends in Electronics and Informatics (ICOEI 2019)
10. Aditi Shah, Prerna Gupta, Prof.Y.M. Ajgar,Dept. of Electronics andTelecommunication, MES College of Engineering, Savitribai Phule Pune University, Pune, India (2018)
11. Yu Sun, Yuan Liu, Guan Wang,and Haiyan Zhang,Hindawi Computational Intelligence and Neuroscience ,2017
12. Hao-Xun Chang, James S. Haudenshield, Charles R. Bowen, and Glen L Hartman,Frontiers in Microbiology,2017
13. Oxford University Press,Giga Science,2018
14. Daniel S. Park, Charles G. Willis, Zhenxiang Xi, John T. Kartesz,Charles C. Davis and Steven Worthington,New Phycologist (2020)
15. ANANDASIVAM GOPAL, MANU GOYAL, MATTHEW REINDORP,Eindhoven University of Technology, Eindhoven, The Netherlands,