IMAGE BASED PLANT DISEASE DETCTION USING CNN

DR.SURESH NARASIMMAN[1]

PROFESSOR, DEPARTMENT OF ECE, AVN INSTITUTE OF ENGINEERING AND TECHNOLOGY, RAMDAS PALLY, HYDERABAD, TELANGANA 501510

ARSHAD KHAN[2]

ASSISTANT PROFESSOR, DEPARTMENT OF ECE, AVN INSTITUTE OF ENGINEERING AND TECHNOLOGY, RAMDAS PALLY, HYDERABAD, TELANGANA 501510

SRIMANTHULA NITESH[3]

UG SCHOLAR, DEPARTMENT OF ECE, AVN INSTITUTE OF ENGINEERING AND TECHNOLOGY, RAMDAS PALLY, HYDERABAD, TELANGANA 501510

TANDELE SITHA RAM[4]

UG SCHOLAR, DEPARTMENT OF ECE, AVN INSTITUTE OF ENGINEERING AND TECHNOLOGY, RAMDAS PALLY, HYDERABAD, TELANGANA 501510

RAMIDI SANDEEP REDDY[5]

UG SCHOLAR, DEPARTMENT OF ECE, AVN INSTITUTE OF ENGINEERING AND TECHNOLOGY, RAMDAS PALLY, HYDERABAD, TELANGANA 501510

M SHIVA SAI[6]

UG SCHOLAR, DEPARTMENT OF ECE, AVN INSTITUTE OF ENGINEERING AND TECHNOLOGY, RAMDAS PALLY, HYDERABAD, TELANGANA 501510

ABSTRACT:

Rapid human population growth requires corresponding increase in food production. Easily spreadable diseases can have a strong negative impact on plant yields and even destroy whole crops. That is why early disease diagnosis and prevention are of very high importance. Traditional methods rely on lab analysis and human expertise which are usually expensive and unavailable in a large part of the undeveloped world. Since smartphones are becoming increasingly present even in the most rural areas, in recent years scientists have turned to automated image analysis as a way of identifying crop diseases. This paper presents the most recent results in this field, and a comparison of deep learning approach with the classical machine learning algorithms

KEYWORDS — machine learning, crop diseases, deep learning.

INTRODUCTION

HUMAN population steadily continues to grow, and along with it the need for food production increases. According to the UN projections [1], human population is expected to reach 9.7 billion in 2050, 2 billion more than today. Considering that most of the population growth is to occur in the least developed countries (around 80% increase in the next 30 years), where the food scarcity is the main problem, it is easy to conclude that minimizing food loss in those countries is a primary concern. It is estimated that the yield loss worldwide is between 20 and 40 percent [2], with many farms suffering a total loss. Traditional methods for detecting diseases require manual inspection of plants by experts. This process needs to be continuous, and can be very expensive in large farms, or even completely unavailable to many small farm holders living in rural areas. This is why many attempts to automate disease detection have been made in the last few decades. One of the notable approaches is the use of hyperspectral imaging. Hyperspectral images are usually taken by satellites or airborne imaging devices and used for monitoring large areas. A downside of this approach is extremely high equipment cost, as well as high dimensionality and small number of samples which make them unsuitable for machine learning (ML) analysis. Because of the recent breakthroughs in computer vision and the availability of cheap hardware, currently the most popular approach is the analysis of RGB images. The other motive for analysing RGB images is that with the current smartphone ubiquitousness these solutions have potential to reach even the most rural areas. RGB images can be analysed by classical ML algorithms or the deep learning (DL) approach. Classical methods rely on image pre-processing and the extraction of features which are then fed into one of the ML algorithms. Popular algorithm choices are Support Vector Machines (SVM), k-Nearest Neighbours (k-NN), Fully Connected Neural Networks (FCNN), Decision Trees, Random Forests etc. In the last few years, the researchers shifted almost exclusively to the DL methods for image classification tasks. The reason is that they almost always outperform classical algorithms when given reasonably sized dataset, and can be implemented without the need for hand-engineered features. In this paper, we compare the DL approach with classical ML algorithms for the study case of plant disease classification.

LITERATURE SURVEY

The global burden of pathogens and pests on major food crops

AUTHORS: Savary, Serge, et al.

Crop pathogens and pests reduce the yield and quality of agricultural production. They cause substantial economic losses and reduce food security at household, national and global levels. Quantitative, standardized information on crop losses is difficult to compile and compare across crops, agroecosystems and regions. Here, we report on an expert-based assessment of crop health, and provide numerical estimates of yield losses on an individual pathogen and pest basis for five major crops globally and in food security hotspots. Our results document losses associated with 137 pathogens and pests associated with wheat, rice, maize, potato and soybean worldwide. Our yield loss (range) estimates at a global level and per hotspot for wheat (21.5% (10.1–28.1%)), rice (30.0% (24.6–40.9%)), maize (22.5% (19.5–41.1%)), potato (17.2% (8.1–21.0%)) and soybean (21.4% (11.0–32.4%)) suggest that the highest losses are associated with food-deficit regions with fast-growing populations, and frequently with emerging or re-emerging pests and diseases. Our assessment highlights differences in impacts among crop pathogens and pests and among food security hotspots. This analysis contributes critical information to prioritize crop health management to improve the sustainability of agroecosystems in delivering services to societies.

Using deep learning for image-based plant disease detection

AUTHORS: Mohanty, Sharada P., David P. Hughes, and Marcel Salathé

Crop diseases are a major threat to food security, but their rapid identification remains difficult in many parts of the world due to the lack of the necessary infrastructure. The combination of increasing global smartphone penetration and recent advances in computer vision made possible by deep learning has paved the way for smartphone-assisted disease diagnosis. Using a public dataset of 54,306 images of diseased and healthy plant leaves collected under controlled conditions, we train a deep convolutional neural network to identify 14 crop species and 26 diseases (or absence thereof). The trained model achieves an accuracy of 99.35% on a held-out test set, demonstrating the feasibility of this approach. Overall, the approach of training deep learning models on increasingly large and publicly available image datasets presents a clear path toward smartphone-assisted crop disease diagnosis on a massive global scale.

A practical plant diagnosis system for field leaf images and feature visualization

AUTHORS: Fujita, E., et al.

An accurate, fast and low-cost automated plant diagnosis system has been called for. While several studies utilizing machine learning techniques have been conducted, significant issues remain in most cases where the dataset is not composed of field images and often includes a substantial number of inappropriate labels. In this paper, we propose a practical automated plant diagnosis system. We first build a highly reliable dataset by cultivating plants in a strictly controlled setting. We then develop a robust classifier capable of analyzing a wide variety of field images. We use a total of 9,000 original cucumber field leaf images to identify seven typical viral diseases, Downy mildew and healthy plants including initial symptoms. We also visualize the key regions of diagnostic evidence. Our system attains 93.6% average accuracy, and we confirm that our system captures important features for the diagnosis of Downy mildew.

Textural features for image classification

AUTHORS: Haralick, Robert M., Karthikeyan Shanmugam, and Its' Hak Dinstein

Texture is one of the important characteristics used in identifying objects or regions of interest in an image, whether the image be a photomicrograph, an aerial photograph, or a satellite image. This paper describes some easily computable textural features based on gray-tone spatial dependancies, and illustrates their application in category-identification tasks of three different kinds of image data: photomicrographs of five kinds of sandstones, 1:20 000 panchromatic aerial photographs of eight land-use categories, and Earth Resources Technology Satellite (ERTS) multispecial imagery containing seven land-use categories. We use two kinds of decision rules: one for which the decision regions are convex polyhedra (a piecewise linear decision rule), and one for which the decision regions are rectangular parallelpipeds (a min-max decision rule). In each experiment the data set was divided into two parts, a training set and a test set. Test set identification accuracy is 89 percent for the photomicrographs, 82 percent for the aerial photographic imagery, and 83 percent for the satellite imagery. These results indicate that the easily computable textural features probably have a general applicability for a wide variety of image-classification applications.

Support-vector networks

AUTHORS: Cortes, Corinna, and Vladimir Vapnik

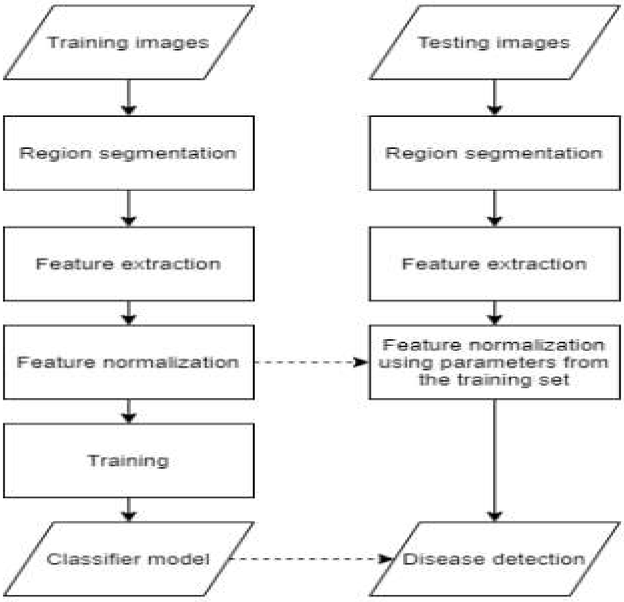
The support-vector network is a new learning machine for two-group classification problems. The machine conceptually implements the following idea: input vectors are non-linearly mapped to a very high-dimension feature space. In this feature space a linear decision surface is constructed. Special properties of the decision surface ensures high generalization ability of the learning machine. The idea behind the support-vector network was previously implemented for the restricted case where the training data can be separated without errors. We here extend this result to non-separable training data.High generalization ability of support-vector networks utilizing polynomial input transformations is demonstrated. We also compare the performance of the support-vector network to various classical learning algorithms that all took part in a benchmark study of Optical Character Recognition.

IMPLEMENTATION

Implementation is the stage of the project when the theoretical design is turned out into a working system. Thus it can be considered to be the most critical stage in achieving a successful new system and in giving the user, confidence that the new system will work and be effective.

The implementation stage involves careful planning, investigation of the existing system and it's constraints on implementation, designing of methods to achieve changeover and evaluation of changeover methods.

ARCHITECTURE



MODULS:

1. **Data preprocessing**
2. **Support Vector Machines**
3. **k-Nearest Neighbours**
4. **Fully Connected Neural Network.**

Data preprocessing:-

Data is stored in colab. We can download the data and laad the datsets , clean the data then after processes the data

Support Vector Machines:-

SVM is a supervised learning algorithm used for classification or regression problems. Classification is done by defining a separating hyperplane in the feature space. In the original form, it performs linear classification on two classes. By using kernels, it can also perform nonlinear classification. Kernels are used for an efficient transformation of the original feature space into high dimensional or infinite dimensional feature space, allowing for highly non-linear hyperplanes. SVM can fit highly complex datasets and at the same time exhibit good generalization propertie.

k-Nearest Neighbours:-

k-NN [7] is a very simple algorithm often used for classification problems. It is both non-parametric (doesn't have a fixed number of parameters) and lazy learning (doesn't have a training phase). k-NN works under the assumption that most samples from the same class are close to each other in the feature space. When determining the class of the sample, k-NN will look at its k closest neighbours and decide to which class it belongs by the simple majority rule. Small values of k will allow for higher non-linearity but will be sensitive to outliers. High values of k achieve good generalization but fail to fit complex boundaries. The best value for parameter k is determined experimentally For this dataset, small values of k were shown to give the best results. Varying k from 1 to 9 doesn't change the accuracy much, with best result being 78.06% much lower than the SVM. We used k=5 in this work

Fully Connected Neural Network :-

FCNN is the simplest type of artificial neural networks. It is a supervised learning algorithm able to model highly non-linear functions. As opposed to SVM and k-NN, it does not converge to the global optimum, but when properly configured, it usually gives good enough results.we used an FCNN with four hidden layers with 300, 200, 100 and 50 neurons per layer, respectively. Activation function in hidden layers is a rectified linear unit (ReLU), with a softmax in the output layer [8]. We used L2 regularization with regularization parameter equal to 0.3. Adam optimizer with default parameters was used This configuration gave us the accuracy of 91.46% on the test set.

CONCLUSION

This paper presents the dominance of the DL method over the classical ML algorithms. Both the simplicity of the approach and the achieved accuracy confirm that the DL is the way to follow for image classification problems with relatively large datasets.

As the achieved accuracy of the DL method is already very high, trying to improve its results on the same dataset would be of little benefit. Further work with the DL model could be done by expanding the dataset with more diverse images, collected from multiple sources, in order to allow it to generalize better.

The considered ML algorithms achieved relatively high accuracy, but with error rates still an order of magnitude higher than the DL model. Further work in improving accuracy of the classical approach can be done by experimenting with other algorithms and by improving the features, as most likely they are the limiting factor of this approach.

REFERENCES

[1]United Nations, Department of Economic and Social Affairs, Population Division (2019). World Population Prospects 2019: Highlights (ST/ESA/SER.A/423).

[2] Savary, Serge, et al. "The global burden of pathogens and pests on major food crops." Nature ecology & evolution 3.3 (2019): 430.

[3] Mohanty, Sharada P., David P. Hughes, and Marcel Salathé. "Using deep learning for image-based plant disease detection." Frontiers in plant science 7 (2016): 1419.

[4] Fujita, E., et al. "A practical plant diagnosis system for field leaf images and feature visualization." International Journal of Engineering & Technology 7.4.11 (2018): 49-54.

[5] Haralick, Robert M., Karthikeyan Shanmugam, and Its' Hak Dinstein. "Textural features for image classification." IEEE Transactions on systems, man, and cybernetics 6 (1973): 610-621.

[6] Cortes, Corinna, and Vladimir Vapnik. "Support-vector networks." Machine learning 20.3 (1995): 273-297.

[7] Cunningham, Padraig, and Sarah Jane Delany. "k-Nearest neighbour classifiers." Multiple Classifier Systems 34.8 (2007): 1-17.

[8] Haykin, Simon. Neural networks: a comprehensive foundation. Prentice Hall PTR, 1994.

[9] Szegedy, Christian, et al. "Going deeper with convolutions." Proceedings of the IEEE conference on computer vision and pattern recognition. 2015.

[10] Duan, Kai-Bo, and S. Sathiya Keerthi. "Which is the best multiclass SVM method? An empirical study." International workshop on multiple classifier systems. Springer, Berlin, Heidelberg, 2005.

[11] Deng, Jia, et al. "Imagenet: A large-scale hierarchical image database." 2009 IEEE conference on computer vision and pattern recognition. Ieee, 2009.