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Plant Disease Detection and Comparison Using DL, ML Techniques

S. Sowjanya[1], B. Aparna[2] Ms.c., M.Tech
[1]Department of Computer Science, Besant theosophical College, Madanapalli, Andhra Pradesh, India
[2]Assistant Professor, Department of Computer Science, Besant Theosophical College, Madanapalli, Andhra Pradesh, India

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ABSTRACT

Crop diseases and pesticides are essential determinants of plant production and quality. Digital image analysis can be used to identify crop diseases and suggest pests. Deep learning is much superior to conventional approaches in recent years of advances in the area of digital image processing. How to study crop diseases and pesticides through deep learning technologies has become a major research topic for researchers. We compare three plants in this project 1) Salvation; 2) Sabdarifa Hibiscus 3) Oleracea brassica for disease detection and pesticide suggestion.This study defines the issue of identification of crop diseases, compares it with conventional plant diseases and methods of detection of pests. This report outlines studies on plant diseases focused on in-depth learning in the last years, based on the disparity in the network structure. In this project we use the CNN model to diagnose diseases of the plants and the disease-related pesticide.

Keywords :- Convolutional Neural Network, Deep Learning, Hygiene Crops.

I. INTRODUCTION

People continue to expand and the demand for food supply grows. The human population is growing. Human population is expected to hit $9.7 billion by 2050, 2 milliards more than today, according to UN estimates. With the majority of population increases in less developed countries (around 80% rise in the next 30 years), which is a major challenge with food shortages, it can be concluded that reducing the lack of food is a major issue in these countries. The world's production loss is expected to range from 20% to 40% with a cumulative loss on several farms.

In farming, leaves play a key role in informing people about the quantity and quality of horticultural production. A number of factors influence food production, including climate change, weed presence and soil infertility. In addition, the rise of many agricultural products and the cause of economic losses is a global danger to plant and leaf diseases. In the future, inadequate use of pesticide/fungicide results in inability to identify infections / bacteria / virus in plants. For this reason, in the scientific community, plant diseases with an emphasis on the biological characteristics of diseases is considered.Precision agriculture utilizes state-of-the-art technologies to optimize decision making. Visual checks and biological examinations are normally performed by means of plant diagnoses, if necessary. However, this procedure is typically costly and time-consuming. In order to tackle these problems, sophisticated and intelligent methods are required to diagnose plant diseases.

Conventional machine learning (ML) algorithms were used in several experiments to execute agricultural operations. Deep learning (DL), however, was recently remarkably successful as a subset of ML for identification, recognition and classification of objects in real life. Agricultural analysis has now moved towards DL-based solutions. DL strategies for agriculture, including crop-weed discrimination, fruit processing and plant identification, have obtained state-of-the-art performances. Likewise, recent studies have also centered on another significant agricultural problem of detection of plant diseases.

Classical approaches are based on image pre-processing, which then is fed into one of the ML algorithms to remove features. Supporting vector machines (SVM), k-Nest Neighbors (K-NN), Fully Connected Neural Networks (FCNN), Decision Trees, Random Forests etc. are common algorithm options. The researchers have switched almost entirely in recent years to DL approaches for image grading activities. The explanation is that, provided the relatively large data collection, they almost often outperform classical algorithms and can be applied without manual functionality.In this paper the DL solution for the research case for classification of plant diseases is compared with classical ML algorithms.

II. RELATED WORKS

Plant disorders [1] inflict significant worldwide agricultural production and economic losses. Sustainable agriculture requires monitoring of health and disease identification of plants and trees. In order to evaluate health conditions in trees in real time, to the best our understanding, there are no commercial sensors available. Scouting is currently the most commonly used tension control device in trees, a costly, time-consuming and labor-intensive procedure. For identifying plant diseases that need thorough sampling and processing, molecular techniques such as polymerase chain reactions.Early information on crop health and disease identification can promote disease management by means of sound management techniques such as pesticide protection, fungicide applications, and disease-specific chemical applications.

Three supervised machine learning algorithms: Decision tree (DT) [2], Random Forestry (RF), and help vector machine comparison of pixel and object-based imaging approaches for classifying diverse land cover classes over agricultural landscapes (SVM). Overall classification accuracies were not statistically important ($p>0.05$) while pixel-oriented or objective-oriented classifications were implemented using the same computer algorithms. The classification quality of the image generated using a DT algorithm was statistically significantly differentiated from the maps produced using RF ($p = 0.0116$) or SVM ($p = 0.0067$), by means of object-based image analysis.There was no statistically significant difference ($p > 0,05$) between results produced using various classification algorithms with pixel-based image analysis. A more visual representation of wetland, riparian and crop land classifications based on the RF and the SVM algorithms has been generated using object-or pixel image processing compared with the DT classifications. This research included lesser variables (15 vs. 300) in pixel-based classifications, similar classification accuracy, and less time to generate than subject-based classification classifications.The visually pleasing, general presentation of land cover groups has been achieved through object classifications. Based only on general precision studies, it was not useful to use a medium-space resolution Earth-watch imaging method instead of a different approach for the mapping of broad-based land cover forms in agricultural ecosystems.

Various advantages [3] to farmers are provided by fully automatic estimated intact fruit yields before harvesting. Several trials to predict fruit yield with picture processing technology have so far been carried out. Most of these strategies include thresholds for color, form and size characteristics. Their efficiency often depends heavily upon the thresholds used, while photos appear to change the optimum thresholds. Furthermore, most of these approaches only tried to identify the mature or immature fruit, although for predicting long-term yield variations the number of young fruits is more important.In this research we were working on a method to detect individual intact tomato fruit accurately, including old, untimely and young Fruits, in combination with machine learning approaches in a plant using a traditional optical RGB camera. For each image fruit sensing, the system established did not involve an adjustment of threshold values because image segmentation was carried out on the basis of classification models created in line with the color, form, texture and image size.

Author [4] introduce deep-learning medical technology here, which focuses on deep learning in computer vision, the processing of natural languages, strengthening learning and widespread approaches. We explain how these technologies can affect some of the main fields of medicine and how end-to-end applications can be developed. Our topic of computer vision focuses mostly on medical pictures and describes the use of fields such as electronic health records and natural language treatment. Robot-assisted surgery also discusses enhanced learning, and generalized methods in deeper learning in genomics are examined.

III. METHODOLOGY

We provide Deep Learning technologies in the proposed scheme, which automatically identify images with the Convolution Neural Network (CNN) models.DL is a family of multi-layer ML algorithms for the purpose of hierarchically acquiring functions. DL algorithms are different but mostly rely on artificial neural networks. Modern applications in the artificial intelligence (AI) industry today are focused primarily on this kind of algorithm. DL models have demonstrated that they can learn highly complex patterns with sufficient data.

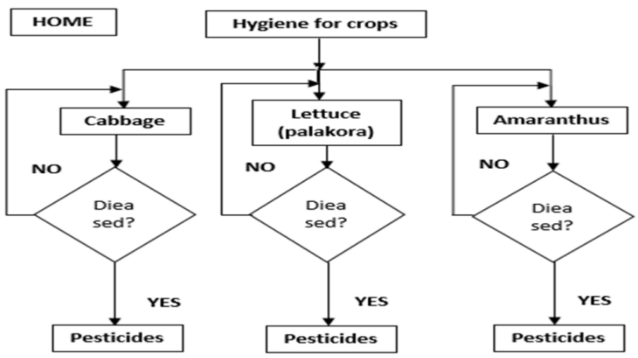

Fig: Block Diagram of Proposed Method

A major benefit of DL algorithms is the fact that they suit incredibly complex models. Feature engineering for DL is not necessary because DL models have raw data and they learn proper features. Convolutionary networks (CNN) are often used for image recognition issues. In this article, we used a GoogleNet models with the configuration parameter presented in to compare it to conventional models. In the ImageNet dataset, we used the weight model. The criteria used include:

- Optimizer: Stochastic Gradient Descent
- Learning rate: 0.005
- Momentum: 0.9

- Weight decay: 0.0005
- Batch size: 24
- Number of epochs: 10

The CNN is a multi-layer Neural network for the identification of complex data features with a special architecture. CNNs have been used in the areas of image recognition, vision and auto drive. The content of different pictures can be rated until a CNN has been produced. Everything we need to do is apply the images to the model. CNNs are founded on the workings of the human brain, including ANNs. CNNs can differentiate images from target identifying tasks through recognition, similar to how the human brain distinguishes.

A. Convolution Operation:

The first building block of the strategy of our assault is convolution activity. The function detectors which are essentially neural network filters are touched on during this process. We can talk about the mapping, know how to observe patterns, how to map the detector and how to map the results.

B. ReLU:

The second component of this mechanism is a rectified linear unit or Relook. In the Convolutionary Neural Networks we will explore Relook layers and how linearity functions.

C. Pooling Layers:

In this segment, we will explore grouping and explain how it normally works. Our nexus here, however, is a special type of bonding. However, we shall explore various approaches, such as medium (or sum) pooling. This section ends in a presentation that definitely works out the whole concept for you on an immersive video interface.

D. Fully Connected:

In this section, all we discussed is fused. You can learn how groundbreaking neural networks operate and how the "neurons" created ultimately learn how to distinguish pictures.

Images were taken outdoors with the normal digital camera and captured from various sources under various weather conditions, rendering the data collection more varied. This data set is suitable for the application of ML algorithms, especially DL samples and different diseases. The downside to this dataset is that each leave was cut and shot under a uniform backdrop, making the circumstances significantly different from those in the field.

IV. CONCLUSION

This report reveals the DL method's superiority over classic ML algorithms. Both the flexibility of its solution and the precision obtained confirm that the DL is the path to follow for relatively large datasets for image classification problems. Given that the DL approach is already extremely accurate, it is of no use to attempt to boost its results in the same dataset. Additional analysis for the DL model should be accomplished, in order to further generalize the data collection with more different images obtained from various sources.The ML algorithms considered have been fairly accurate, but with error rates they still exceed the DL model in the order of magnitude. Furthermore, experiments with other algorithms and functionality may be carried out to improve the precision of a classical solution, since they most certainly are the only restricting aspect.

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