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Smart Agriculture Using Deep Learning and Machine Learning Techniques.

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Abstract:* This study analysed the recent research articles on deep learning techniques in agriculture over the previous five years and discussed the most important contributions and the challenges that have been solved. Furthermore, we investigated the agriculture parameters being monitored by the internet of things and used them to feed the deep learning algorithm for analysis. Additionally, we compared different studies regarding focused agriculture area, problems solved, the dataset used, the deep learning model used, the framework used, data preprocessing and augmentation method, and results with accuracy. We concluded in this survey that although CNN provides better results, it lacks in early detection of plant diseases. To cope with this issue, we proposed an intelligent agriculture system based on a hybrid model of CNN and SVM, capable of detecting and classifying plant leaves disease early. - Farming productions are a necessary employment in industrial and for employment. The Internet of Things (IoT) has the capability to convert the methods we stay in the universal. We have additional-effective manufacturing, greater associated vehicles, and smoother townships, a lot of these as Flavors of an integrated Internet of Things (IoT) system.

Keywords: Internet of Things (IOT), Smart Agriculture, Machine Learning, Deep Learning

1. INTRODUCTION

Internet of Things (IoT) is a mechanism of computing strategies that are related from each dissimilar. These computing devices must be strength-strapped in addition to digital technologies and these computing devices can transmission Information over a network disadvantaged of disconcerting human-to-human or human-to-computer Oral conversation. Kevin Ashton, in a presentation of Procter & Gamble in 1999, invented the period "Internet of Things". Virtually each area, device, instrument, software, and so forth are related to respectively other. The forthcoming to admittance these devices through a phone or finished a computer is declared to as Internet of Things (IoT). These devices are recovered from are serve. For example, an In-flight Conditioner's device container gets the documentations concerning the out of doors hotness, and for this reason modify its hotness to prosperous or decrease it with esteem to the out of doors climate.
Internet of Things (IoT) technology has understood the smart wearable's, connected devices, automatic machines, and driverless automobiles. However, in farming, the Internet of Things (IoT) has presented the supreme result. With the arrival of Industrial IoT in Farming, a long way more larger sensors are being applied. The sensors are now connected to the cloud thru mobile/satellite TV for pc community. Which we could us to realize the actual-time information from the sensors, making decision making powerful.

Fig 1: Smart Agriculture using IOT

The programs of internet of Things (IoT) in the farming inventiveness has aided the agriculturalists to small screen the liquid container levels in real-time which makes the irrigation method additional well-ordered. The improvement of Internet of Things (IoT) generation in agriculture operations has added the use of sensors in each stage of the agriculture technique like how a lot time and properties a seed receipts to turn out to be a totally- full-grown plant. Smart Agriculture is a hello-tech and real means of accomplishment farming and growing food in a sustainable method. It is a
Usefulness of applying linked implements and inventive equipment cooperatively interested in farming. Smart Farming majorly depends on Internet of Things (IoT) as an importance casting off the need of biological landscapes of growers and cultivators and therefore growing the productivity in every attainable means. In this paper we look at the effect of IoT in agriculture.
In recent years, smart agriculture has flourished in several areas. Furthermore, deep learning applications in smart agriculture have spread widely and yielded advanced, satisfactory results. This paper intends to survey and analyse deep learning techniques and their applications in agriculture to be a modern and comprehensive reference for researchers.
This survey work is conducted in three steps. The first step involved collecting relevant research by searching keywords (agriculture, deep learning, convolutional neural networks, recurrent neural networks, crop monitoring, disease detection, and irrigation systems). Keyword-based searches were performed for journal and conference papers from the IEEE Xplore and ScienceDirect scientific databases and the Web of Science and Google Scholar scientific indexing services. A total of 70 articles were collected that were later reduced to 60, which presented some deep learning models. We studied these papers and further narrowed the numbers to 40 papers that conducted deep learning experiments and provided some results. In the second step, the selected scientific papers were analysed and compared in terms of:
The areas of smart agriculture that were focused on.
The problems that they tried to solve.
The deep learning techniques and models used.
The dataset used.
The data preprocessing and data augmentation methods that were used.
The results in terms of accuracy or precision.
In the third and last stage, we found that some weaknesses and shortcomings existed in surveyed papers, and we tried to suggest some improvements to overcome these issues. As an output of this survey, we proposed a hybrid deep learning model consisting of CNN and SVM that is expected to improve existing models' performance and working range.

2. REVIEW OF LITERATURE

Data gathering, data pre-processing (i.e., data preparation that includes feature extraction), and ML classification models are the three basic steps of ML applications, represented in Figure 1. The following sections present and discuss different approaches used in these three stages.

Figure 2. Simplification of the ML pipeline.

Data Acquisition

Data acquisition is the process of gathering data from various sources systems [26]. Previous studies gather their data various sources to be used for ML techniques. Some of them produce their own images by taking pictures of plants in greenhouses, such as in the studies from Gutierrez et al. and Raza et al. [5]. However, image data acquisition using manual processes, as done by many, generally results in small image data-sets, which can compromise the development of effective ML-based models. Weather data collection is also proposed in the literature using for instance sensors in greenhouses. Meteorological data can also be obtained from weather stations of regional areas, which typically store records for a longer period of time.

Images can be collected using search engines on their own. This approach can get a large number of images, but ground truth must be checked by domain experts, and data cleaning is frequently used to filter out images that do not meet the requirements.

Remote sensing images from satellites and drones have the advantage of being able to retrieve image data for large agricultural areas. Remote sensing data from satellites typically consists of multi-temporal and hyper-spectral imagery data, which can be used to assess the development of the crops. This task can be performed by monitoring the evolution of vegetation indices, which provide important information about the development status of the crop fields. Spectral imagery can be used for computing different vegetation indexes, such as those proposed in, which are robust to variations on the sun illumination, an important advantage when compared to visible light spectrum imagery.

Images retrieved from drones can also be used, but have additional needs: to define the path of the device; to coordinate the drone position with the camera for image acquisition; and to correct geometric distortions on each acquired image in order to merge the different acquired images in order to reconstruct a larger image of the whole field.

Therefore, it can be stated that data consists of different modalities and variables. With ML-based and data analysis techniques it can be possible to understand their interaction and how they relate to a studied outcome. In the context of the cultivation fields, the questions are usually: which disease is affecting crops? What pest is causing damage? What is the relation between weather data and disease and pest occurrence?

Freely available data-sets can also be utilized for the development of ML-based applications. This enables researchers to directly compare the performance of different ML techniques and approaches. The data conditions a significant impact on the performance of ML models. Data-sets should be representative and include enough records for the model to perform an effective generalization.

Plant diseases and pest development are greatly influenced by weather and environment conditions. Humidity is a favourable condition for the development of fungus diseases. The humidity can be caused by the weather or by poor watering practices that cause a high wetness among the leaves, making tomatoes more susceptible to diseases, e.g., leaf mold or bacterial spot. In addition, temperature is a primary driver of insect development, affecting their metabolic rate and population growth [6].
Plants absorb part of the radiation coming from the sun and reflect the rest. Depending on the health of the plant, the amount of radiation absorbed and reflected differs. This difference can be used to distinguish between healthy and diseased plants and to assess the severity of the damage.

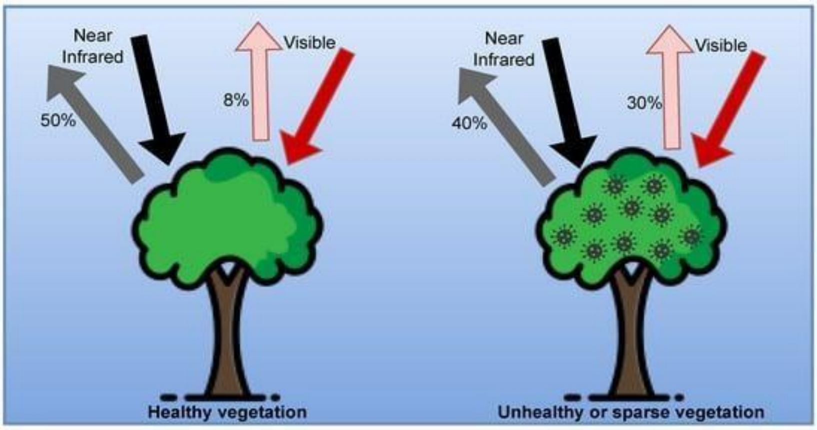

Figure 3. Absorbed and reflected radiation for plant's health estimation.

3. METHODOLOGY

Data Pre-Processing:
Data pre-processing techniques vary according to the used ML-based approach. In the case of image data, feature extraction can be done manually by applying computer vision algorithms, or automatically using deep learning.

Manual feature extraction processes typically demand pre-processing steps such as noise reduction or contrast enhancement. The researchers have to decide and select which feature extractors are more suitable for the problem at hand. When using deep learning, pre-processing is typically focused on data augmentation, enriching the training data-set in order to achieve a better model generalization. Deep learning shows better results when directly analyzing the originally acquired images when compared with the use of images converted to grey-scale or subject to background removal. This is a useful finding because background removal can be a complex and arduous task for images taken in field conditions, with complex and varying background. When comparing the performance of ML models based on manual feature selection with models based on deep learning, the latter has shown better performance in studies that compared both approaches using the same input data.

Highlighting the region of interest of the leaves and reducing the background noise can increase the model's performance. This is valid for plant disease identification as well as for insect classification.

Machine Learning Models:
The studies presented along this paper have mostly used SVM, RF, or deep learningbased ML models. All of these have shown promising results, highlighting the potential of using ML techniques for disease and pest classification, detection, and prediction. SVMs are robust and useful in high dimensional spaces due to their use of kernel trick. RF can avoid overfitting due to the high number of trees trained in different subsets of data. Deep learning usually achieves the best classification results due to its ability to create and extract hierarchical features from the inputs. Deep learning beats other ML models, particularly in image classification domains, especially when using pre-existing CNN architectures such as Inception and ResNet.
Despite deep learning models achieving higher accuracy values, SVM and RT can also achieve high values with accuracy above 94%, especially in disease classification on laboratory images. SVM also achieves high accuracy, with values above 90%, in the detection of tomato diseases. RNNs are capable of establishing relationships between weather data and pest occurrence, surpassing other models such as RF and SVM.

In scenarios where data is difficult to obtain, models trained with a lower amount of data can benefit from the use of TF, rather than having the models trained from scratch. Most studies have their models pre-trained on large data-sets for image classification such as ImageNet or COCO. The inclusion of the PlantVillage data-set with ImageNet for pretraining helps to improve the accuracy of models for disease classification on images acquired in the field. TF is typically applied by training some of the top layers of the pretrained model jointly with the new classifier. An alternative would be to address lack-of-data problems using few-shot learning approaches, as suggested in [3].

4. CONCLUSION AND FUTURE SCOPE

This survey presented an insight into existing research addressing the application of MLbased techniques for forecasting, detection, and classification of diseases and pests.

Data-sets containing weather, diseases, and pests' data should keep records for long periods of time. Time-series ML models, such as RNN, can be employed to accurately forecast the occurrence of diseases and pests based on meteorological measurements series. NDVI measurements can also be helpful, since they provide additional information regarding the crop's development.

Detection and classification of pests and diseases can be performed using computer vision and deep-learning algorithms based on CNN models, which show better performance when compared with older image classification approaches based on "manual" features extraction. However, deep learning models require large amounts of data, which can be difficult to obtain. To tackle this issue, the use of transfer learning or few-shot learning methods can prove useful. Nonetheless, although the performance of deep learning-based methods is high for images acquired under controlled conditions, additional research is required regarding the analysis of images taken in the field, under real life conditions. Since the literature does not yet include substantial work on pest and disease forecasting using combinations of different data modalities, this article also aimed to provide a general overview on the use of ML techniques over different types of data, in order to facilitate further developments that may help fulfill this gap.

5. REFERENCES

[1] Plant diseases and pests detection based on deep learning: a review Jun Liu and XueWei Wang, Article number: 22 (2021)

[2] Machine Learning for Detection and Prediction of Crop Diseases and Pests: A Comprehensive Survey, Tiago Domingues, Thomas Brandao, Joao Ferreira, Agriculture (2022)

[3] Review on Emerging Trends in Detection of Plant Diseases using Image Processing with Machine Learning, Volume 174 – No. 11, January 2021 39, Punitha Kartikeyan, Gyanesh Shrivastava.

[4] Gutierrez, A.; Ansuategi, A.; Susperregi, L.; Tubío, C.; Rankić, I.; Lenža, L. A benchmarking of learning strategies for pest detection and identification on tomato plants for autonomous scouting robots using internal databases. J. Sens. 2019, 2019, 5219471.

[5] The Support Vector Machine (SVM) Based Near-Infrared Spectrum Recognition of Leaves Infected by the Leafminers, Wu Dake; Ma Chengwei

[6] Deutsch, C.A.; Tewksbury, J.J.; Tigchelaar, M.; Battisti, D.S.; Merrill, S.C.; Huey, R.B.; Naylor, R.L. Increase in crop losses to insect pests in a warming climate. Science 2018, 361, 916–919. [Google Scholar] [CrossRef] [PubMed]

[7] Xiao, Q.; Li, W.; Kai, Y.; Chen, P.; Zhang, J.; Wang, B. Occurrence prediction of pests and diseases in cotton on the basis of weather factors by long short-term memory network. BMC Bioinform. 2019, 20, 688. [Google Scholar] [CrossRef]

[8] Krizhenvshky A, Sutskever I, Hinton G. Imagenet classification with deep convolutional networks. In: Proceedings of the conference neural information processing systems (NIPS), Lake Tahoe, NV, USA, 3–8 December; 2012. p. 1097– 105.

[9] Szegedy C, Liu W, Jia Y, Sermanet P, Reed S, Anguelov D, Erhan D, Vanhoucke V, Rabinovich A. Going deeper with convolutions. In: Proceedings of the 2015 IEEE conference on computer vision and pattern recognition, Boston, MA, USA, 7–12 June; 2015. p. 1–9.

[10] Simonyan K, Zisserman A. Very deep convolutional networks for large-scale image recognition. arXiv. arXiv:1409.1556. 2014.

[11] Xie S, Girshick R, Dollár P, Tu Z, He K. Aggregated residual transformations for deep neural networks. arXiv. arXiv:1611.05431. 2017.