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Identification of Diseases to the Crops Using Machine Learning

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ABSTRACT:

Considering the population growth rate of recent years, a doubling of the current worldwide crop productivity is expected to be needed by 2050. Pests and diseases are a major obstacle to achieving this productivity outcome. Therefore, it is very important to develop efficient methods for the automatic detection, identification, and prediction of pests and diseases in agricultural crops. This paper presents a literature review on ML techniques used in the agricultural sector, focusing on the tasks of classification, detection, and prediction of diseases and pests, with an emphasis on tomato crops. Thissurvey aims to contribute to the development of smart farming and precision agriculture by prom oting the development of techniques that will allow farmers to decrease the use of pesticides and chemicals while preserving and improving their crop quality and production.

INTRODUCTION:

Due to extremely high infant mortality, the human population of the planet increased slowly until the year 1700. The first billion was reached in ca. 1800, followed by the second billion in 1928, the third billion in 1960. In 2017, the world's population reached its seventh billion [1]. The fast population growth over recent decades is mainly due to better medical care. According to predictions from the United Nations, the world's population is expected to reach 9.7 billion in 2050, and 10.9 billion in 2100. Rapid population growth over recent decades has resulted in an increased demand for agricultural goods, which in turn has lead to a large expansion of cultivation [2]. To meet rising population demands for food, bio-fuels, and animal products, crop yield production must double its output by 2050. In order to achieve this goal, key crop yields must improve by 2.4% each year, but they are now only increasing by roughly 1.3% per year. However, fulfilling this condition will have negative consequences for the ecosystem, including the loss of biodiversity and increased greenhouse gas emissions [3]. Traditional agricultural production is not sustainable from an economic or environmental standpoint; hence, it is critical to optimize the use of resources such as water and soil to enable high yield crops . Moreover, crop output is continually threatened by diseases and insect pests. It is estimated that between 20% to 40% of yearly crop production is lost due to plant diseases and insect assaults across the world, costing the global economy $220 billion and $70 billion, respectively [4]. The amount of these losses varies across the globe and often occurs due to

transboundary plant pests and diseases. For instance, the spread of crop pests and pathogens between 1950 and 2000 was greater in North America when compared with other world regions. Pest damage and development are affected by the rise in global temperature brought by climate change [5]. When the temperature rises, the metabolic rate of insects increases. The traditional method of detecting and identifying plant diseases involves naked eye observation by experts. This takes time and talent, and is not a practical solution for monitoring large farms [6]. Therefore, to overcome the limitations of manual detection, automated methods for crop monitoring and forecasting are required [7]. A system capable of performing such tasks can play an important role in avoiding the excessive use of pesticides and chemicals, reducing both the damage caused to the environment and the production costs associated with the use of pesticides and chemicals . The growing availability of big data analysis methods has the potential to spur even more research and development in

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smart farming [8]. Besides promoting higher yield crops in a more sustainable manner, it also aims to contribute to event forecasting, detection of diseases, and management of water and soil [9]. Big data is coming to the agriculture domain by collecting from meteorological stations, remote sensors, historical data, and publicly available data-sets [10].

ML approaches have been successfully utilized in a variety of areas, including illness detection from medical images [11], image classification on large data-sets, self-driving automobiles, and academic research fields such as physics

LITERATURE REVIEW:

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 [12]. The following sections present and discussdifferent approaches used in these three stages.

Data acquisition ,Data pre-processing , Machine Learning Model Clasification.

1. Data Acquisition

Data acquisition is the process of gathering data from various sources systems . 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..

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

Absorbed and reflected radiation for plant’s health estimation (adapted from). Temperature Insects are ectothermic, meaning that they cannot regulate their internal temperature and have to rely on environmental heat sources. Temperature affects the population growth and metabolic rates of insects . Thus, the duration of an insect’s life cycle is highly influenced by the number of days where the temperature is suitable for its development. Two temperature thresholds can be define: an upper threshold, in which insect development slows down or stops and a lower one where there is no insect growth. These thresholds vary according to the specific insect species. Degree day is a concept concerning the accumulation of heat by insects. One degree day is a period of 24 h in which the temperature was one degree above a given baseline. Different models for determining the number of degree days associated to commonpest species were proposed in . For instance, tomato crops are susceptible to the greenhouse white fly (Trialeurodes vaporariorum), whose number of degree days from egg to adult is 380 DGG. Depending on the temperature of the environment, this development time can be longer or shorter. Biofix date is the date to start accumulating degree days associated with a given insect species. This date can be determined by noticing specific insect species on traps or by detecting eggs on plant leaves. From this date, degree days can be used to estimate the period at which insects are reaching a given development stage suitable for pesticide application. Temperature and weather forecasts are nowadays sufficiently accurate to enable the estimation for the time required for an insect to reach a given development status .

. Agriculture Data-Sets :

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Many data-sets used in the context of agriculture include images of plant diseases or pests with the goal of classifying them. PlantVillage, PlantDoc, IP102, Flavia and, MalayaKew Leaf are some data-sets that are freely available. Here is a brief summary of each of these: • PlantVillage popular data-set used for plant disease classification. Specifically for tomato, it contains 18,160 images representing leaves affected by bacterial spot, early blight, late blight, leaf mold, septoria leaf spot, spider mites, two-spotted spider mite, target spot and tomato yellow leaf curl virus. It also includes

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images of healthy leaves. Figure 3 depicts two sample images taken from this data-set. • IP102 : data-set for pest classification with more than 75,000 images belonging to 102 categories. Part of the image set (19,000 images) also includes bounding box annotations. This is a very difficult data-set because of the variety of insects, their corresponding development stages (egg, larva, pupa, and adult) and image backgrounds. The data-set is also very imbalanced. Figure 4 presents two examples of images from this data-set. • PlantDoc: contains pictures representing tomato diseases which were acquired in the fields. Among the considered diseases are: tomato bacterial spot, tomato early blight, tomato late blight, tomato mold, tomato mosaic virus, tomato septoria leaf spot, tomato yellow virus and healthy tomatoes.

2. Image Segmentation:

Image segmentation is the process of grouping pixels into regions of interest. In the context of crop disease identification, these regions of interest can be, for instance, diseased areas on the plant leaves, for assessing the severity of the infection by the amount of the infected area, or for background removal, since the removal of the background allows highlighting of the regions of interest for further analysis. An example of background removal.

CONCLUSIONS:

This survey presented an insight into existing research addressing the application of ML-based 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. De. However, deep learning models require large amounts of data, which can be difficult to obtain. To tackle thisissue, 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 requiredregarding 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 aimedto 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.

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