A COMPREHENSIVE STUDY OF ADVANCED TECHNIQUES FOR PLANT HEALTH MONITORING USING DEEP MACHINE LEARNING TECHNIQUES

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Abstract: Plant diseases cause significant production and economic losses in agricultural industries worldwide. Health monitoring and disease detection of plants and trees is important for sustainable agriculture. This review describes current technology that can be used to develop soil sensor systems to help monitor plant health and disease under field conditions. There are several leaf diseases responsible for the damaging the crop and leaf rust is one of the major diseases which can destroy the entire wheat crop. Leaf diseases in crops can be predicted more quickly and accurately, which could lead to the development of an early treatment method and a significant reduction in economic losses. Advancement in computer vision technologies has offered new dimensions in the direction of developing a decision support system that can assist in identification and detection of plant diseases in early stage. The use of computer vision and pattern recognition to detect disease has been studied in an effort to reduce losses and achieve intelligent healthy farming. Deep Learning models are widely used for the identification of plant leaf disease detection. However, still researchers, experts and farmers face challenges when trying to deploy the trained deep learning models in agriculture filed, in order to tune the model for achieving better results on huge datasets. Majority of the deep learning models provide poor testing results if there is some variation (rotation, tiling, and other abnormal image orientations) in scanned images.

Keywords: *Classification, Detection, Image Processing, Plant Disease.*

1. INTRODUCTION

Agriculture will need to produce approximately 50% more food by 2050 as a result of the increase in the world wide population. India is primarily an agriculturally oriented nation, with agriculture employing seventy percent of the people. Plant diseases have become a concern because they can cause a significant reduction in the quality and quantity of agricultural products, which affects the economies of countries that depend on agriculture for their capital. get. All disease symptoms attract attention and cause concern because of their effect on grain or grass and quality.

The development of computer systems in recent years, especially those with integrated graphics processing units (GPUs), has led to a rapidly increasing number of artificial intelligence applications related to machine learning, leading to the development of new, developing methods and models. now a new group known as deep learning has been formed[1]. When it comes to artificial neural network architecture, deep learning refers to those with a large number of processing structures, unlike the "swallow" architecture used by traditional neural network architecture. . Deep learning models, which can now be computed, have changed areas such as image recognition [2], speech recognition and other complex methods that consider the analysis of large data, and -give a big boost. applications that use these techniques, such as autonomous vehicles, machine translation and interpretation, and other similar techniques. The application of these deep learning methods in agriculture [3], and especially in the field of plant disease diagnosis, has only recently started, and is very limited, compared to other areas. Deep learning methods are increasingly being used to solve machine vision challenges. Various researchers have previously investigated the plant and leaf identification using various methodologies. Initially, color information was employed to identify the plant from the soil in these difficulties[4]. Deep learning is a relatively recent approach to plant and leaf identification.

Despite their best efforts, these artificial neural networks fall far short of the capabilities of the human brain when it comes to "learning" from vast amounts of data. It's possible to improve accuracy by using more than one hidden layer of neural network. In many AI apps and services, deep learning is used to improve automation by performing analytical and physical tasks without the need for human intervention. One of the machine learning methods is deep learning. Many layers of data are used in deep learning to extract useful features from the raw data, which is then used to recognize various input data elements. Deep learning methods include convolutional networks, recurrent neural networks, and deep neural networks.

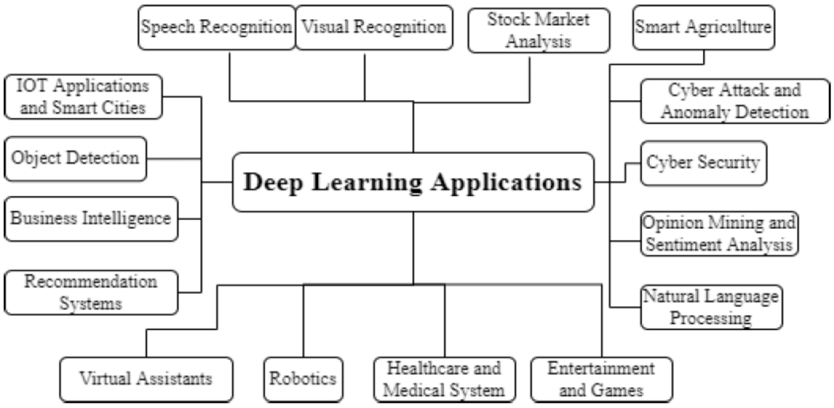

Figure 1. Application of deep learning

2. LITERATURE REVIEW

This disease can also spread to other plants. The bacterial infection is more difficult to find than the fungal infection because bacteria are so small that it is hard to see them[5]. The first and most accurate diagnosis of plant diseases using artificial neural networks (ANN) and image processing techniques[6] demonstrated. To accomplish the best outcomes, the proposed technique depends on fake brain organization (ANN) for arrangement and Gabor channel for highlight extraction. Different plant illnesses are characterized by ANN characterization that utilizes a mix of surface, variety and different highlights to recognize these infections.

Techniques for leaf-based disease detection are proposed[7]. Random forest is the algorithm used in this proposed work to identify healthy and infected leaves in images. Data identification, feature extraction from leaf images, data extraction of function and classifier and classification are the proposed phases of work. Random forest algorithm and grouping of infected and healthy videos are used to create datasets of infected and stable or healthy leaves. In order to extract useful features from images, the histogram-oriented gradient (HOG) was used. The SVM algorithm is a recent addition to the classifier in the neural network approach to problems involving detection and accuracy in classification.

Augmentation Process. The fundamental reason for applying expansion is to build the dataset and bring less twisting into the picture, which assists with diminishing the size during the preparation interaction. In AI, and in measurements, restrictions emerge when factual strategies depict commotion or arbitrary mistake as opposed to the hidden relationship [8]. Picture joining comprises of one of a few change strategies, including relative change, viewpoint change, and straightforward picture change.

3. ROLE OF DEEP LEARNING IN AGRICULTURE AND PLANT DISEASE DETECTION

Deep learning methods are increasingly being used to solve machine vision challenges. Various researchers have previously investigated the plant and leaf identification using various methodologies. Initially, color information was employed to identify the plant from the soil in these difficulties [9]. The morphology of veins was used in some investigations[10]. The leaf veins include a variety of texture and form features that can help with plant identification using eyesight. The shape information was also utilized in certain leaf-based research. Several researchers[11] integrated the shape and texture information retrieved from the leaf, while others used color and texture information [12]. The main goal of hyperspectral analysis of plant diseases is from cellular to regional. In general, there are two main aspects involved in the hyperspectral detection of plant diseases: (I) to distinguish infected plants from healthy plants and (II) to detect specific diseases among others. The first condition affects only one type of plant and one virus and the second condition focuses only on one virus, classifying all other possibilities as areas of indifference. For non-graphical hyperspectral data, the representation of healthy and diseased parts of the body must be obtained separately, and the analysis usually spans leaf, plant, and field scales. For the selection of the classification algorithm, according to previous studies in the diagnosis of plant diseases using hyperspectral imaging methods, the simplest and most commonly used is the segmentation of the image is the boundary segmentation.

Plant sickness conclusion incorporates distinguishing proof, grouping and characterization, and is one of them Picture division is utilized as a pre-handling procedure, normally performed prior to checking an example to separate an objective item from the foundation or make a cover for district of interest (return for capital invested) handling for recovering extra data. Highlight extraction is a strategy for decreasing the quantity of elements in a dataset by extricating new ones from existing elements (and erasing the first elements).

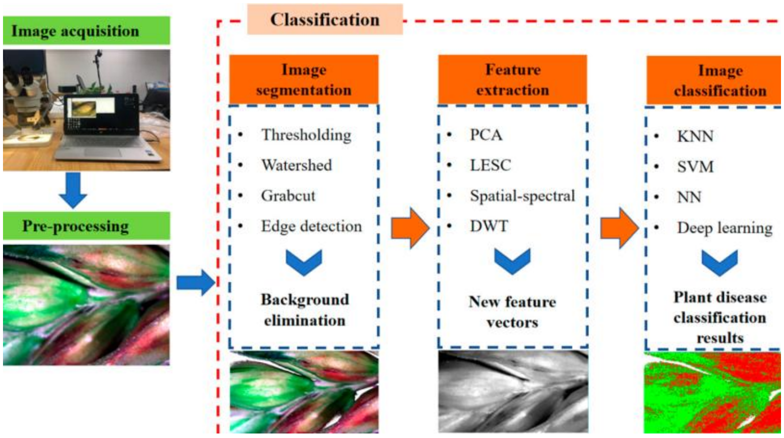

Figure 2.1. workflow of hyperspectral imaging plant disease.

The main list of capabilities will actually want to sum up the vast majority of the data in the new list of capabilities. From the summation of the first elements, a synopsis form of the first highlights can be created. It is one of the mainstays of the ID and characterization of articles by hyperspectral imaging [13-17]. In this way, in the characterization of plant illnesses in view of hyperspectral pictures, the principal highlights incorporate the appearance, yet in addition spatial elements, text highlights and other data that can be gotten with the assistance of picture information.

Image processing and plant disease diagnosis based on hyperspectral images include techniques which separates the data into health groups and different types of pathogens or diseases. The above-mentioned image segmentation is often done in production methods to improve the performance of data analysis, which is not always necessary in the diagnosis of plant diseases.

In artificial intelligence (AI), and notably in machine learning, it is permissible to use information and experience obtained from solving one problem to assess and handle other related (and even unrelated) problems and difficulties. This is an AI and ML phrase referred to as "transfer learning" [18-21]. To make research more effective in a setting where computational resources are limited, this practice is becoming increasingly prevalent. Models that have already been trained can be re-used to fill in the gaps.

Numerous techniques are right now utilized for plant illness finding utilizing PC vision. One of them is sickness analysis by separating variety highlights as shown by the creators [22]. In this article, the YcbCr, HSI, and CIELB tones are utilized in the review; thus, the illness spot is recognized well and isn't impacted by clamor from various sources, for example, camera streak.

Plant illnesses can be analyzed by fostering a progression of side effects. Patil and Bodhe applied this technique for sickness determination in sugarcane passes on where they utilized edge division to recognize leaf region and three-sided limit for sore region, accomplishing a typical exactness of 98.60% in the last examination.

ANNs as a method for a programmed discovery and grouping of plant sicknesses was utilized related to implies as a bunching system proposed by the creators in [23]. By and by, there is a business arrangement, which involves visual acknowledgment to distinguish tree species from their leaves' pictures however as the organization introduced in this paper is ordering the plant illnesses rather than kinds of plant, Leafsnap was not utilized for examination of the accomplished outcomes. Atomic strategies for plant illness location have been widely settled[23-26]. The awareness of the atomic techniques alludes to the most reduced amount of microorganism that can be distinguished in the example. The for the most part involved sub-nuclear methods for contamination acknowledgment integrate ELISA and PCR (PCR and consistent PCR) (PCR and steady PCR). Other sub-nuclear procedures consolidate immunofluorescence (IF), stream cytometry, fluorescence in situ hybridization (FISH), and DNA microarrays[27]. In the ELISA-based disease acknowledgment, the microbial protein (antigen) associated with a plant disorder is imbued into an animal that makes antibodies against the antigen. These antibodies are assembled from the animal's body and utilized for antigen conspicuous evidence using a fluorescent tone and mixtures.

Fluorescence of citrus leaves was assessed for 60 days under four specific conditions: leaves with no strain, leaves with mechanical tension, leaves with contamination, and passes on with ailment notwithstanding mechanical strain. The assessments revealed the capacity of fluorescence spectroscopy for illness end and detachment between the mechanical and hypochondriac strain.

The ML models help to set up the model and give us incredible results. The photos dealt with into the model will be ready by the components isolated and it will be ready. The model used in the assessment have shown basic progression and results.

To portray the plant prosperity, the plant have relatively few component like length of the leaf, size of the leaf and the assortment reflected from the plant. In this assessment we have taken out the assortments bunches from the image that would be valuable to recognize the sufficiency of the plant[28-29].

With regards to hyperspectral information imaging, environment handling, mathematical amendment, and unearthly handling are the three fundamental parts of hyperspectral information handling. Environmental change centers around surface reflectivity blunders of air dissipating and retention applied to satellite information investigation; Mathematical rectification centers around mathematical mutilations brought about by soil changes, stage slant, and so forth. It is likewise utilized in field, low-level, airborne, and satellite information examination.

This large number of physiological and biochemical markers are dynamic changes all through the entire development time of yields. The extraordinary development time frame and exceptional status have their unique attributes. Accordingly, SVIs are viewed as the lists that mirror the development phase of plants in remote detecting. Direct model fitting and game plan are the earliest and most intuitionistic approaches in quantitative end. To analysis the illness seriousness by direct model fitting and grouping, measurable strategies and AI calculations are generally utilized. Since measurable techniques are easy to see hypothetically and yield noticeable outcomes, they are for the most part utilized in sickness seriousness measurement

4. CONCLUSIONS

Plant diseases cause critical monetary and post-gather misfortunes in horticultural regions. Creation area on the planet, particularly affected by environmental change age. This article reviews and summarizes some of the methods used to diagnose plant diseases. The review shows that these diagnostic methods have good potential to detect plant diseases effectively. Studies show that these symptomatic techniques have huge likely in the capacity to analyze plant sicknesses precisely. Spectroscopic and imaging innovation can be incorporated into an independent farming vehicle for solid, continuous plant sickness identification to accomplish progressed plant infection the executives. There are numerous strategies for programmed or fake vision location in the administration of plant sicknesses, however this exploration region is as yet uncommon. The utilization of profound learning strategies to naturally extricate and recognize plant sicknesses from leaf pictures was explored. The expansion of this study will zero in on the assortment of pictures to further develop information capacity and work on the precision of the model utilizing different handling and streamlining techniques. Additionally, future work will build the utilization of the model via preparing it to perceive plant sicknesses across the land, by joining aeronautical photographs of plantations and grape plantations caught by rambles with convolutional neural network disclosure.

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