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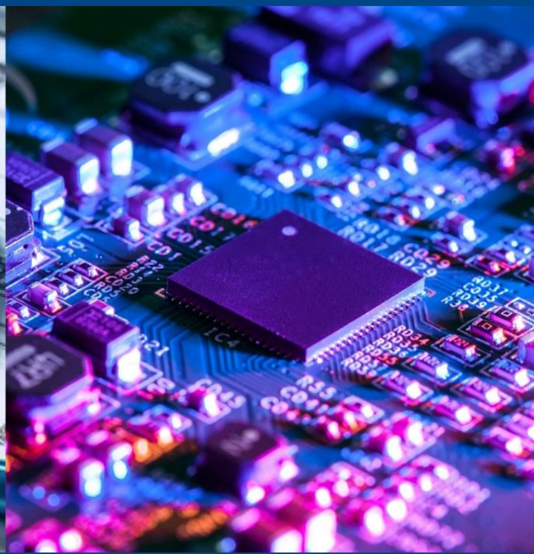

International Journal of Multidisciplinary Research in Science, Engineering and Technology

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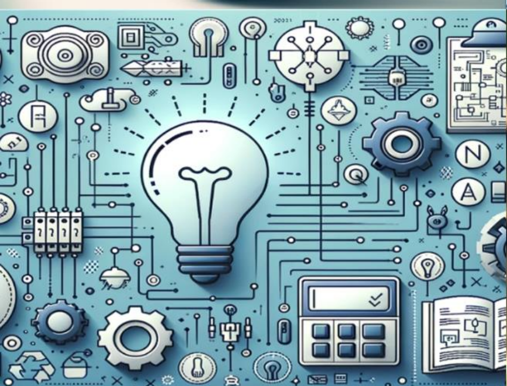

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Crop Disease Prediction

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ABSTRACT: The process is proposed and implemented image processing technique using OpenCV for separating the diseased part of the crop from the image of the crop. Foreground Extraction, Feature extraction and classification is done for crop images. This novel technique can facilitate the process of the detection of diseases in crops. The system allows to follow a particular pattern of capturing images of plants so that threats will be analysed quickly. This process will ultimately contribute in semi-automation of agriculture processes faster and will make farmers to cultivate more in less amount of time.

KEYWORDS: HTML, CSS, Bootstrap, Python ML.

I. INTRODUCTION

The application of computer science and automation to the field of agriculture is a crucial part of precision agriculture. Processes like planting of crop seeds in a field through machinery, fertilization, spraying of pesticides to preserve the crops, and ultimately harvesting, all have the properties of being repetitive and precise in nature. These properties make these processes suitable for automation without much human intervention and labor. To automate guidance systems for machinery like tractors, and harvesters, plant and crop row detection is an important step. The separation of crop plants from weeds is crucial for site specific pesticide treatments and curbing excessive use of chemicals that could result in destroying the crop plants in addition to weeds. The detection of plants and crop rows is affected by several environmental conditions. Shadows and poor lighting conditions affect image quality. Weeds with similar spectral signatures can also be present in the field, interspersed between the crop plants, making the process of separation a challenge, thereby producing erroneous crop rows. The terrain and topography of the field also affect the image quality and pose a challenge for machinery to navigate through. Different plant heights and volumes due to difference in growth stages can also create severe problems. Under the above mentioned adverse environmental conditions and even with irregular inter-row spaces, supervised and unsupervised methods were compared for the segmentation of the crop field images to detect plants, thereby facilitating the demarcation of straight crop rows in the field.

A standard artificial neural network (ANN) model consists of many neurons (connected processors), each producing a sequence of real-valued activations. When sensors perceive environment changes, input neurons will be activated and other neurons will then get activated through weighted connections from previously active neurons. Depending on the specific problem and the neuron topology, these behaviors may require long chains of computational stages, where each of the stage transforms the aggregate activation of the network. DL is about how to accurately assign credit across many such stages. Deep learning allows computational models that are composed of multiple processing layers to represent data with multiple levels of abstraction. Great improvements of the method can be found in many research domains. The concept of BP (Back Propagation) Neural Network is the basis for many DL algorithms. With massive enthusiasm pouring into the DL field, great improvements have been achieved in recent years. DL has drawn a lot of attention in agriculture. One of its applications in agriculture is image recognition, which has conquered a lot of obstacles that limit fast development in robotic and mechanized agro-industry and agriculture. These improvements can be seen in many aspects of agriculture, such as plant disease detection, weed control, and plant counting. Researchers in agriculture may not be experienced programmers. They often directly use publicly available software frameworks for deep learning without carefully examining the learning mechanisms used. An understanding of DL algorithms can facilitate data analysis and thus enhance research in agriculture. Although various commercial software frameworks are available, there is a lack of a systematic summary of major DL algorithms, including concepts, application limitations, flow charts, and example codes, which can help researchers in agriculture to learn major DL techniques quickly and use them effectively.

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II. EXISTING SYSTEM

- **PlantVillage and Nuru by FAO**
  By: David Hughes & FAO (Food and Agriculture Organization) **Overview**:
  A mobile-based AI solution designed to help farmers detect plant diseases using a smartphone camera and machine learning. Developed as part of the PlantVillage platform.
- **Deep Learning-Based Disease Detection Using PlantDoc Dataset**
  By: Akash Durga, Jainendra Shukla, and team **Overview**:
  Research that applies deep learning models like **ResNet**, **MobileNet**, and **InceptionV3** to detect diseases from plant leaf images using the publicly available PlantDoc dataset.

Real Time Examples:
Plantix App – Mobile app to detect crop diseases using leaf images
Nuru by FAO – AI-based app that works offline to identify plant diseases
IBM Watson Agriculture – Predicts disease outbreaks using weather and soil data
Drone Surveillance – Uses cameras to spot diseased crops from above

III. NEED OF THIS PROJECT

Crop disease prediction is very important in agriculture because it helps farmers protect their crops before the disease spreads. Every year, many farmers lose a large part of their harvest due to unexpected diseases. By predicting diseases early, farmers can take the right steps to save their crops and avoid big losses. It also helps reduce the overuse of pesticides, which is better for the environment and saves money. Disease prediction improves the quality and quantity of crops, which leads to better income for farmers and more food for everyone. With the help of new technology like mobile apps, sensors, and AI, crop disease prediction is becoming easier and more accurate. It also helps farmers face challenges caused by changing weather and climate conditions.

IV. PROPOSED SYSTEM

The disease-free growth of a plant is highly influential for both environment and human life.

However, there are numerous plant diseases such as viruses, fungus, and micro-organisms that affect the growth and agricultural production of a plant. Grape esca, black-rot, and isariopsis are multi-symptomatic soil-borne diseases. Often, these diseases may cause leaves drop or sometimes even vanishes the plant/plant vicinity. Hence, early detection and prevention becomes necessary and must be treated on time for better grape growth and productivity.

In addition, the treatment is recommended when the types of disease are classified for actual disease/symptoms. This results in recommended the remedies according to the diseases..

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VI. ADVANTAGES

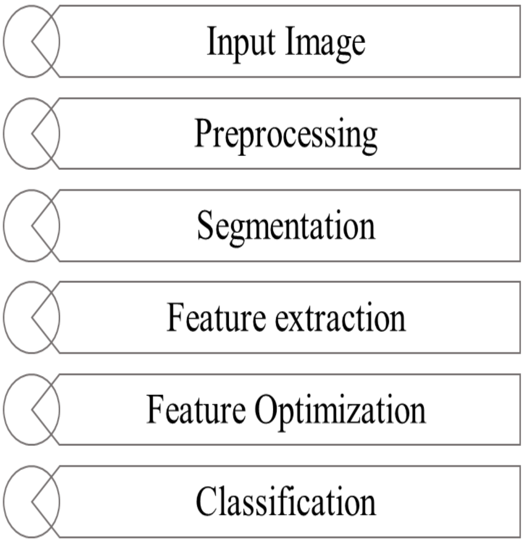
- The accuracy of the process is more when compared with the existing method.
- The reliability of the process is well optimum due to the limited number of dataset is used.

VI. METHODOLOGY

The methodology for solving the problem for Crop Disease Prediction could include the following steps:

1) **Input Image:** Read an image into the workspace, using the imread command. The example reads one of the sample images included with the toolbox, an image, and stores it in an array named I . imread infers from the file that the graphics file format is Tagged Image File Format (TIFF).
2) **Preprocessing:**
3) **Image Resize:** Resizing an image is done using software to add or subtract pixels, and is called resampling. When an image is resampled it increases or decreases the width and height of the image in pixels. There are other ways to resize an image, such as by cropping it to a smaller size. Hence in this process, image is resized into 256 X 256, i.e. the number of pixels in the row is equal to 256 and then the number of pixel in the column is equal to the 256.
4) **Feature Extraction:** Local binary patterns (LBP) is a type of visual descriptor used for classification in computer vision. LBP is the particular case of the Texture Spectrum model proposed in 1990.
5) **Classification:** "Support Vector Machine" (SVM) is a supervised machine learning algorithm that can be used for both classification or regression challenges.

VII. ARCHITECTURE DIAGRAM



VIII. CONCLUSION

The reason for developing such system is to identify and reuse weed affected area for more seeding.
This specific area can be considered for further weed control operations, resulting in more production.
The experimental results show that this method with K-means pre-training achieved 92.89% accuracy, beyond 1.82% than convolutional neural network with random initialization and 6.01% than the two layer network without fine-tuning.
Our results suggest that identification accuracy might be improved by fine-tuning of parameters

Future work:
In the future, crop disease prediction can be improved by using advanced techniques like deep learning and combining models for better accuracy. Real-time detection with sensors and drones can help monitor diseases immediately.

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Expanding datasets to include various crops, diseases, and climates will make the system more adaptable. Integration with farm management tools can assist farmers in decision-making, and weather data can help predict disease outbreaks. Feedback from farmers will improve the system over time, while low-cost, offline solutions will increase accessibility. Making predictions easy to understand will help farmers trust and use the system effectively.

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