Fertilizer Recommendation System for Disease Prediction

Introduction:

Detection and recognition of plant diseases using machine learning are very efficient in providing symptoms of identifying diseases at its earliest. Plant pathologists can analyze the digital images using digital image processing for diagnosis of plant diseases. Application of computer vision and image processing strategies simply assist farmers in all of the regions of agriculture. Generally, the plant diseases are caused by the abnormal physiological functionalities of plants. Therefore, the characteristic symptoms are generated based on the differentiation between normal physiological functionalities and abnormal physiological functionalities of the plants. Mostly, the plant leaf diseases are caused by Pathogens which are positioned on the stems of the plants. These different symptoms and diseases of leaves are predicted by different methods in image processing. These different methods include different fundamental processes like segmentation, feature extraction and classification and so on. Mostly, the prediction and diagnosis of leaf diseases are depending on the segmentation such as segmenting the healthy tissues from diseased tissues of leaves.

Literature Survey:

Wang et al (2022) [1] used YOLOv5 model to improvise the speed and accuracy on classifying plant diseases. They proposed an IASM mechanism to improve the accuracy and efficiency of model and used Ghostnet and WBF structure to speed up the learning efficiency. The model obtained an F1 score of overall 92.65% (using self-made dataset) and compared with existing models such as Faster R-CNN, VGG16, SSD, YOLOv4 and YOLOv5. The model performed well in overall and the researchers concluded that the scope can be extended to suit the current scenario.

Shah et al (2022) [2] proposed an architecture termed ResTS (Residual Teacher/Student) that can be used as visualization and a classification technique for diagnosis of the plant disease. ResTS is a tertiary adaptation of formerly suggested Teacher/Student architecture. ResTS is grounded on a Convolutional Neural Network (CNN) structure that comprises two classifiers (ResTeacher and ResStudent) and a decoder. This architecture trains both the classifiers in a reciprocal mode and the conveyed representation between ResTeacher and ResStudent is used as a proxy to envision the dominant areas in the image for categorization. The experiments have shown that the proposed structure ResTS (F1 score: 0.991) has surpassed the Teacher/Student architecture (F1 score: 0.972) and can yield finer visualizations of symptoms of the disease.

Mondal et al (2022) [3] proposed an ensemble-based CNN architecture which can detect plant diseases from plant leaf images. It considers CNN models like VGG16, ResNet-50 and InceptionV3 as base models and the prediction from these models is used as input for Inception-ResNetV2 (author’s meta model) which helped them to achieve an accuracy of

97.9% (ReLU) under test conditions. The model can be improved by incorporating image segmentation techniques for easier classification.

Isinkaye et al (2022) [4] designed and implemented a user-friendly smartphone-based plant disease detection and treatment recommendation system using machine learning techniques. CNN was used for feature extraction while the ANN and KNN were used to classify the plant diseases; a content-based filtering recommendation algorithm was used to suggest relevant treatments for the detected plant diseases after classification. The result of the implementation shows that the system correctly detected and recommended treatment for plant diseases.

Aftab et al (2022) [5] used image processing techniques to treat plant diseases at early stage using images captured from Raspberry PI device. The Raspberry PI is used to connect the camera to the display device, from which the data is sent to the cloud. Various procedures, such as acquisition, pre-processing, segmentation, and clustering, are used to examine the acquired images. As a result, the demand for labour in big farm areas is reduced. Also, the cost and effort are reduced, whereas productivity is increased. Various procedures, such as acquisition, pre-processing, segmentation, and clustering, are used to examine the acquired images. As a result, the demand for labour on huge farmlands is reduced. Costs and efforts are also minimized, while production is raised. The model (Faster CNN and SSD Mobile net) achieved an accuracy of 99% in overall.

References:

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