Abstract

ABSTRACT

Agriculture improves the global economy but faces economic, social and ecological losses from plant leaf diseases. Manual identification and controlling strategies for leaf diseases are costly in terms of time and potential for mistakes. As a result, automated classification of multiple leaf diseases is necessary for enhanced productivity. Many different pre-trained Convolutional Neural Networks (CNNs) have been employed by scientists to categorize leaf diseases and pests. However, the effectiveness of such models becomes lessened when leaf images are of low quality. To address this issue, researchers created a Dual-Attention and Topology-Fusion with Generative Adversarial Network (DATAGAN) that uses several pre-trained CNN classifiers to produce high-resolution leaf pictures and label them according to illness kind. But it did not learn the spatial correlations across a series of image samples since diseases affected only a part of the leaf or the whole. Also, it was highly sophisticated for farmers to make decisions on classified leaf diseases and use proper pesticides to control pests, which are the major sources of disorders affecting the leaves. The primary goal of this study is to new adversarial deep learning (DL) systems may improve the accuracy with which crop leaves are inspected for signs of pests and diseases, and to propose pesticides for maximizing agricultural yields.

The primary scholarly advance of this study is the proposal of a Positional-aware DATFGAN (PDATFGAN) model to locate a set of coordinates that resembles the latent distribution manifold. The generator in this model generates pictures of leaves using the pixel position and orientation as criterion, thus the model's name, Positional-aware GAN (PGAN). Following the sampling of a latent vector, the generator imposes position and orientation constraints on each pixel in order to produce patches at each of the resulting spatial locations. Additionally, the discriminator learns to prioritise the boundaries between patches when deciding whether they are consistent and permanent. High-resolution picture patches are created and pieced together to create the whole leaf image. As a result, DATFGAN with conditional coordination has a better shot of creating high-quality pictures

than DATFGAN alone. To further categorize the various leaf diseases, the acquired leaf pictures are fed into pre-trained DCNN models like ShuffleNetV2, DenseNet121, and MobileNetV2.

Second, this study contributes a novel model called PDATF-Evolutionary GAN (PDATFEGAN), which optimizes the generator and produces high-resolution images of leaves by using different objectives. Adopting an Evolutionary GAN (EGAN) that treats adversarial learning as an evolutionary issue is the main change. A discriminator may stand in for the air, and the population of generators will change as a result of the discriminator's influence. When it comes to reproducing and adjusting to their environment, the generators play the role of parents and carry out various mutations to create new generations. Losses between the simulated and real-world picture distributions may be minimized by using a variety of adversarial goal functions based on a wide range of mutation tasks. The updated progeny's image quality and variety are calculated for an ideal discriminator. After then, the "survival of the fittest" idea turns in and the poorly conducting progeny are thrown out while the "fittest" are kept for future education. By preserving the best progeny produced by different learning goals, PDATFEGAN overcomes the difficulties associated with using adversarial learning methods. Pre-trained deep convolutional neural network (DCNN) models are then used to the images to diagnose leaf diseases.

In the third contribution of this research, a unified pest detection and crop leaf disease classification model is proposed to improve crop productivity successfully. The PDATFEGAN's high-resolution photos of infected leaves are only one example of the multi-dimensional datasets used in this model; others include pest, soil, and weather information. The Multi-dimensional Feature Learning-based DCNN (MFL-DCNN) model is fed these datasets to learn the association between pests and leaf diseases. In addition, a softmax classifier is trained to distinguish between pests that cause different leaf diseases.

Finally, this research improved upon previous work by developing a hybrid of the Multi-Functional Logic-Neural Network (MFL-DCNN) and the Rough Set (RS) on a Fuzzy approximation space (RSF)-based decision support system to advise on appropriate pesticides for various leaf diseases and pests. By projecting the most effective pesticide for a given crop in a given location with varying soil and climatic conditions, it facilitates sound decision-making for the management of leaf diseases and pests. The RSF method takes into account many different factors—from the kind of leaf disease to the local temperature, soil, and pests—in order to provide an optimal management strategy. The suitable pesticide is advised to manage leaf diseases and pests based on the association between these multi-dimensional data features detected using the rules that were developed. To increase crop yields, farmers may use this MFL-DCNN-RSF model to determine which pesticides are most effective against various leaf diseases and pests. Finally, the proposed models are evaluated against state-of-the-art models by using PVD, soil, insect, weather, and pesticide datasets. The experimental results reveal that when compared to the various versions of recommended models and state-of-the-art models on multi-dimensional datasets, the PDATFEGAN with MFL-DCNN-RSF achieves 98.93% accuracy.