Literature Survey on Recognizing the Plant Leaf Diseases in Digital Images

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ABSTRACT

Digital image_processing techniques when applied to the digital images reveal diverse patterns that lead to the identification and classification of plant leaf diseases. This research conducts a literature review of twelve algorithms that use color, texture, shape, and hybrid approaches to identify between good and diseases leaves while measuring their effectiveness.

Keywords: color, texture, shape, digital images, classification.

1. INTRODUCTION

"Modern technology have enabled human society to produce enough food to feed more than 7 billion people. Climate change, pollinator decline, plant diseases, and other factors, among others, continue to threaten food security. Plant diseases are a global threat to food security, but they can be especially damaging to smallholder framers whose livelihoods are reliant on healthy crops. Smallholder farmers account for more than 80% of agricultural production in developing nations, with yield losses of up to 50% due to pests and disease being common." Furthermore, half of all hungry people live in smallholder agricultural households, making smallholder farmers particularly vulnerable to pathogen-related food disruptions. Efforts have been made to develop effective disease-prevention strategies integrated pest management (IPM) tactics have increasingly supplemented traditional approaches of extensive pesticide application over the last decade. "Whatever method is employed, correctly detecting an diseases when it first appears is crucial for efficient disease management. Disease identification has usually been helped by agricultural extension agencies or other institutions such as local plant clinics. Such efforts have been boosted in recent years by making disease diagnosis information available online, leveraging the worlds rising internet connectivity. Even more recently, mobile phones-based tools have emerged, taking advantage of the historically unprecedented rapid adoption of mobile phone technology throughout the globe. Because of their computer power, high-resolution displays, and comprehensive built-in sets of accessories, such as powerful HD cameras, Smart_Phones in particular offer quite unique techniques to helping identify diseases." By 2020, it is expected that the world will have between 5 and 6 billion smart phones. "Mobile broadband penetration reached 47 percent in 2015, a 12-fold increased from 2007, Because of the ubiquitous use of smart phones, high-definition cameras, and high-performance processors in mobile devices, disease diagnosis based on automatic picture recognition might be made available on an unprecedented scale, if theoretically viable. The project plant village made 54,306 photos of 14 crop species with 26 illnesses (or healthy) publicly available to test the technical feasibility using a Deep Learning approaches." For segmentation of plant disease spots, agricultural plant leaf disease 2017 detection utilizing image processing in which texture statistics are computed from Spatial Gray- level Dependence Matrix (SGDM) and Artificial Neural Network (ANN) etc. K-Means algorithm is used to segment leaves. The Gray Level Co-Occurrence Matrix (GLCM) is used to extract texture features, while Support Vector Machine (SVM) is used to classify them. Various scholars have presented various strategies for automatic leaf picture segmentation and disease identification. Machine Learning in 2020 comprises a variety of methods, but the Convolution Neural Network (CNN) model is utilized to diagnose disease from photos since it produces the best results. AlexNet, VggNet, ResNet, LeNet, and Sequential model are the five algorithms employed. Machine learning appears to be a superior choice for solving the problem in 2021. To automatically identify and classify plant diseases from digital plant pictures, several Machine Learning (ML) algorithms are presented. Different diseases harm plants in their leaves. Several ML algorithms have recently been presented for identifying and classifying plant diseases from plant pictures. These automated technologies have fixed the concerns, but the bigger challenge is ensuring that the test findings are consistent and reliable.

2. LITERATURE SURVEY

Some of the related work carried out by other researchers are as follows. Plant disease detection and classification using image processing methods contains a few steps as image acquisition, image_processing, segmentation, feature extraction and classification. Using Image Processing techniques, the illnesses of brinjal leaf are identified using a K-Means clustering algorithm [1] for segmentation and a Neural-Network for classification. (i) Digitizing the disease leaves color image. (ii) The images are segmented. (iii)

Using a color images of a disease spot on a leaf to extract texture, shape, and color properties. (iv) Classify and distinguish between various disorders. The accuracy rate is 90%. viral, fungal, and bacterial illnesses such as Alternaria, Nthracnose, Bacterial spot, and Canker are the most common plant diseases. K-Means segmentation is used to segment the sick area. The textural characteristics of the Gray-Level Co-Occurrence Matrix (GLCM) are retrieved, and classification is performed using Support Vector Machine (SVM) [2]. the approach has been put to the test for detecting illnesses in citrus leaves. The accuracy rate is 98.27%. artificial Neural Networks (ANN), Support Vector Machine (SVM), Content-Based Image Retrieval (CBIR Method), K-Nearest Neighbor (KNN), Probabilistic Neural Network (PNN), Scale-Invariant Feature Transform (SIFT), Bayes classifier, and FUZZY LOGIC [3] are some of the diseases classification techniques that can be used for plant_leaf diseases detection. The usage of genetic algorithm [4] for addressing optimization problems in machine learning is employed for image segmentation used for automatic detection and classification of plant illness, which is crucial for disease detection on plant leaf diseases. The accuracy rate is 95%. Support Vector Machine (SVM) was used to identify and diagnose illnesses of grape leaf [5]. Re-sizing, thresholding, and Gaussian filtering are used to process images in the supplied system. The leaf region is segmented using the K-means clustering technique, and then characteristics are extracted using both texture and color data. Finally, the type of illness is determined using the SVM classification approach. Downy Mildew and Powdery Mildew were the two types of grape leaves studied in this experiment. The accuracy rate is 88.89% on average. The method detects diseases from infected apple_leaves by integrating machine_learning and image processing techniques to categorize both infected black rot and cedar apple rust and non-infected healthy apple leaves, with image segmentation acting as a pre-processing stage. Otsu thresholding and histogram equalisation are used in Multiclass SVM [6]. The Otsu approach is a clustering-based image thresholding in which a Multiclass SVM distinguishes the disease type from the original leaf_image among 500 photos with approximately 96% accuracy. Potato disease identification using a Convolution Neural Network [7] based on a classification approach called legitimate sequential model. The accuracy rate is 97%. The CNN model [8] is used to detect disease from photos of potato leaf categorization because it produces the best results. AlexNet, VggNet, ResNet, LeNet, and Sequential model are among the five algorithms employed. Image_Processing and Machine_Learning CNN techniques were used to detect and classify potato leaf diseases. The accuracy rate is 99%. Picture processing approaches based on image_segmentation, CNN, clustering, and open-source algorithms were used to diagnose tomato plant leaf disease [9]. The accuracy rate is 98%. Plant leaf disease identification using image processing techniques [10] looks at diseases in Maize, Arecanut, Coconut trees, Papaya, Cotton, Chilli, Tomato, and Brinjal. The images of plant disease illustrate several variants leaf diseases such as Rust, Kole Roga, Yellow-leaf disease, Leaf-rot, Leaf-curl, Angular-leaf spot, Leaf-spot, Late-Blight, Bacterial wilt. The diseased portions of leaves, as well as the input photos with a complex background, are processed in a sequential manner. Pre-processing, Clustering, Cluster_selection, and Extraction of damaged leaf area are the primary components of this method. For a classification-based strategy to detect and quantify the severity of late_blight disease in potatoes, Fuzzy C-Means Clustering (FCM) and Neural Network techniques [11] were utilized. The accuracy rate is 93%. By measuring the measure of intensity variation at the pixel of interest, the contents of the GLCM matrix [12] can be utilized to calculate texture features. The accuracy rate is 80.45%. On Kaggle datasets of potato and tomato leaves, Convolutional Neural Network (CNN) models such as AlexNet and ResNet-50 [13] were deployed. The system uses AlexNet and ResNet-50 architectures to classify the processed leaf pictures into potato early blight, potato late blight, tomato early blight, and tomato late blight. The precision is 95.3%. Image processing and machine learning approaches are useful for properly identifying the custard apple leaf disease. Custard apple leaves are prone to anthracnose, leaf_holes, leaf_spots, brown_edges, nutritional deficiencies, and other diseases. The accuracy is 89.23%. The machine_learning algorithm performs better since it can handle multi-dimensional and multi-variety in a dynamic context. The SVM and K-means clustering [14] are used in the machine learning approach to classify diseases and predict leaf status. The accuracy is 89.23%. Downy_Mildew, Powdery_Mildew, Black Rot, and other diseases are frequent in grape plants. Multiclass SVM (MSVM) [15] are used to classify diseases found in grapevines in order to make Decision Support Systems (DSS) more automated and accessible to farmers. The system takes a single leaf as input and uses a high_pass filter to segment the leaf to detect the unhealthy zone. The texture of the segmented leaf is retrieved using fractal-based texture features, which are spatially invariant in nature and so provide an excellent texture module. The collected texture_pattern is subsequently sorted into healthy and pathological classifications using Multiclass SVM classifiers. An experiment result demonstrates the use of Multiclass SVM to integrate image processing techniques with Decision Support System (DSS). the goal of this project is to develop an automated DSS that can distinguish between healthy and unhealthy leaves quickly and easily for farmers. The accuracy rate is 96.66%. The Decision Tree model is used in the Knowledge-Based system acquired using Data_Mining technique [16]. The experiment uses the J48 model with 10-fold cross-validation to classify 16 features of infected leaf symptoms from 129 leaf image datasets into three categories: (i) Normal-Leaf, (ii) Anthracnose, and (iii) Decision-Tree. There are 129 leaf image attributes in the datasets, which are divided into three answer classes: normal_leaf, anthracnose, and algal_spot. The decision-tree model now provides six critical features to employ for classifying leaf symptoms after implementing the J48 algorithm on Weka3.8. The accuracy rate is about 89%. The system primarily consists of image processing such image acquisition, image pre-processing, image_segmentation, feature_extraction, classification, and the GLCM [17]. Farmers are having trouble manually diagnosing plant diseases, thus machine-learning techniques [18] and algorithms are being utilized to identify and classify plant diseases from digital plant pictures. The classifier utilized in this case is the Support Vector Machine (SVM). Attempts to develop a unique approach for predicting plant diseases using machine learning techniques. The leaves images were downloaded from the internet and used as a training dataset. The first few images from dataset are taken and features are extracted, there are four distinct classes. The disease Alternaria or Alternata is represented by class 0; Anthracnose is represented by class 1; Bacterial Blight is represented by class 2; and healthy_leaves are represented by class 3. the findings of the experiments suggest that plant diseases may be diagnosed accurately. The Random Forest Classifier [19] model is a supervised learning technique for classification and regression issues. It is used to train with an accuracy of about 70%. To create an automated and easily accessible system, image segmentation with Multiclass SVM [20] is used. With a little computational effort, the two most important potato diseases, late blight and early blight and and early blight, can be recognized. The model had a classification accuracy of around 95%. The Generative Adversarial Network (GAN) and Deep Convolution Neural Network (Deep CNN) [21] examines the use of GANs on 2789 images of tomato plant disease. An image translation configuration for synthetically augmenting the plant disease dataset and employing deep CNN to increase performance on the plant disease recognition assignment. To achieve satisfactory results, the insecure training procedure necessitates numerous standards. The model was able to classify with an accuracy of 86.1%. The Deep Convolution Neural Network [22] technique classifies and detects plant diseases from leaf images automatically. The model has a classification accuracy of 96.3%. The Deep Convolution Encoder Network (DCEN) [23] was used to identify disease in crops like potato, tomato, and maize using plant village datasets. The model had a classification accuracy of around 97.5%. A comparative study between CNN, SVM, Decision Tree and K-NN reveals 97%, 97%, 90.3% and 80% respectively. Convolution Neural Network [24] for tomato leaf disease detection, there are three convolution and max pooling layers in a CNN-based architecture, each with a different number of filters. Because of an activity like pooling, a CNN is essentially slower. Accuracy is 91.2%. In Convolution Neural Network (CNN) [25] model segmented and annotated images are used instead of full images. The model could classify with an approximate accuracy of 98.60%. Without the use of the Internet, a real-time deep learning-based model [26] for identifying and classifying important corn diseases has been developed. To lower the severity if losses and eliminate crop health concerns, Artificial Neural Network (ANN) solutions with smart algorithms for corn plant disease identification are essential. The accuracy is 88.66%. The Particle Swarm Optimization (PSO) algorithm [27] has proved successful in identifying and categorizing diseases in sunflower plant leaves. It does not require any prior knowledge of the number of segments, as other approaches do. The best outcomes were achieved with little computational effort. Combining or hybridizing PSO with other methods, such as gradient search, may produce faster results. The accuracy rate is 98%. Pattern recognition, classification, and object extraction are just a few of the challenges that computer vision with machine learning approaches has outperformed in solving. The mango leaves affected with the fungal disease Anthracnose were processed using a Multilayer Convolution Neural Network (MCNN) [28] classifier. The precision is 97.13%. The CNN and Learning Vector Quantization (LVQ) algorithm [29] methods are used for tomato leaf disease detection and classification. The LVQ method uses of 500 feature vectors extracted from original images for training and testing operations. To do classification, the trials were carried out on healthy and diseased leaf images. LVQ is a supervised classification techniques technique based on prototypes. The model could categorize with an accuracy of about 86%. Apple plant diseases are detected from images of apple plant leaves and accurately classified into four classes using the Deep Convolutional Neural Network models EfficientNet and DenseNet [30]. "Healthy", "Scab", "Rust", and "Multiple diseases" are among the classifications. Deep CNN models can extract and merge information without the usage of complicated filtering techniques. To avoid over-fitting, data augmentation is essential for high accuracy. The model had a classification accuracy of around 99.75%. The K-means technique, GLCM, and SVM are used to detect diseases in plants [31]. Segmentation_techniques such as K-means clustering are used to extract various features. The GLCM and SVM classifiers are used to categorize different sorts of diseases. The method aids in the diagnosis of a variety of diseases in leaves. The model had a classification accuracy of 96.41%. Image segmentation Support Vector Machine (SVM) classifier, ResNet and VGG convolutional neural network model [32] identifies and classify apple leaf diseases. Residual Network (ResNet) is one of the famous deep learning models. A convolutional neural network model is VGG-16. when the training accuracy of ResNet-18 and ResNet-34 is compared, it is discovered that ResNet-18 has superior recognition accuracy and a lower loss rate. Later, the same data set was verified using the VGG-16 method, and it was discovered that the ResNet approach had a greater recognition result. The model had a classification accuracy of 98.5%. The K-means clustering approach is used to segment the images, and characteristics are generated from the disease-affected cluster. For cotton and tomato diseases, the Neural Network (NN) classifier [33] extracts features such as contrast, correlation, energy, homogeneity, mean, standard deviation, and variance. The model was able to categorize with a 92.5% accuracy. Computer_Vision developed using deep learning has a technique of detecting and diagnosing problems in plants by using a camera to capture images as a basis for recognizing different forms of plant diseases. Using a convolutional neural network, detect and recognize the 32 different plants kinds and plant diseases [34]. The model had a classification accuracy is 96.5%. The GLCM and a simplified fuzzy ARTMAP neural network as a classifier are used to identify and classify plant leaf diseases [35]. The GLCM and texture_feature equation are employed as statistical data in a simplified fuzzy ARTMAP to correctly categorize four different types of grape leaf disease images. The model had a classification accuracy of around 90%. Support Vector Machine (SVM) [36] was implemented for classification of the turmeric leaf diseases. The textual analysis of leaf photos was done using the Gray Level Co-occurrence Matrix (GLCM), and a library leaf images was constructed and processed using K-means image-segmentation. The SVM classifier is used to categorize the feature extracted images after they have been sorted using an information gain approach. To depict the many stages of the image processing method and detect the two leaf diseases, a Graphical User Interface (GUI) was designed. The model had a classification accuracy of about 91%. The Support Vector Machine (SVM) classifier is used for machine_learning, and the results are examined using multiple SVM Kernels. For segmentation, the Hue Saturation Value (HSV) and L*a*b* color models have been used. The techniques employed are Pattern Recognition, Color Based Detection, Image Processing, and K-means Clustering [37]. The Plant Village datasets is used, which includes images of grape plant leaves that have been afflicted by Block_Rot disease as well as healthy leaves. The Hue Saturation Value Scale gives a numerical representation of the image that matches the color names. L*a*b* is another name for the CIE LAB color space. The letters L* and a* and b* stand for the four distinct colors of human vision: red, green, blue, and yellow. Sensitive yo non-uniform light. Color differences are not always linear. Other nonlinear transformations have a singularity problem. The model could categorize with an accuracy of 94.1%. The performance of classifiers Support Vector Machine (SVM), Random Forest (RF), and Artificial Neural Network (ANN) [38] is compared on the same datasets of potato leaves. In diseases detection, ANN has the maximum accuracy of 92%. The accuracy of SVM is 84%, whereas the accuracy of RF is 79%. Because of its ability to understand and learn complicated real-time systems, ANN is the best classifier with the maximum accuracy of 92%. One example of how Computer_Vision and Machine learning might help farmers is the employment of a Deep_Learning algorithm [39] to detect and classify whether a sugarcane-leaf is diseased or healthy. The model had a classification accuracy of almost 95%. Develop a Deep Convolutional Neural Network (DCNN) called LeNet [40] to discover the tea_plant diseases from leaf image set. The LetNet refers to LeNet-5 is a convolutional neural network (CNN). The accuracy of CNN classifiers in diagnosing diseases various tea leaves from image sets status was tested using Receiver Operative Curve (ROC). The model could classify with approximate 90.23% accuracy.

3. CONCLUSION

A thorough review strongly explains an enormous methodologies used in computing the features for recognizing the unhealthy and healthy structure of the leaves with their efficiency.

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