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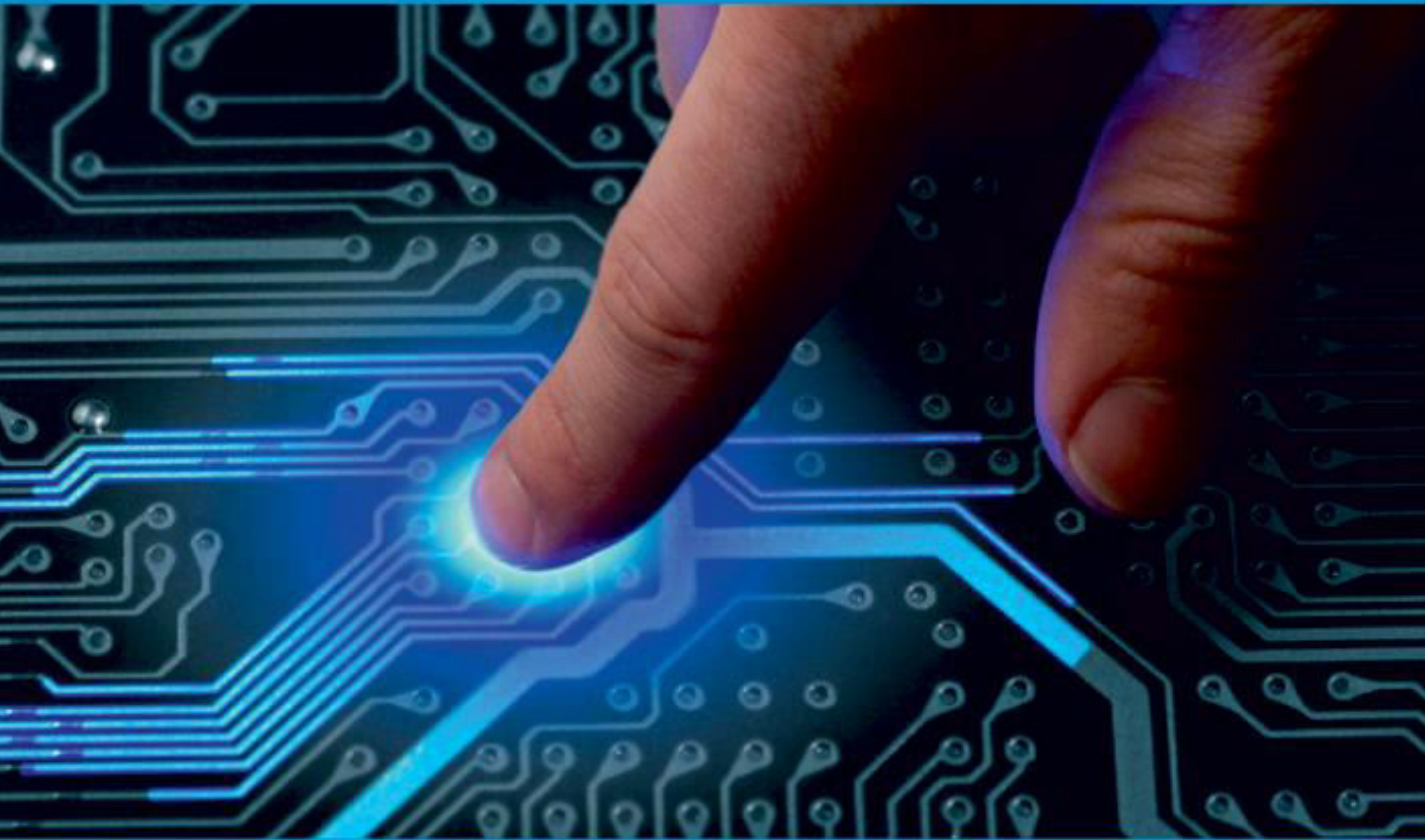

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Agricultural Development Using IOT

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ABSTRACT: Plant diseases are responsible for a 35% yearly crop production loss in India. It is challenging to identify plant diseases early since there is a shortage of lab infrastructure and knowledge. In this study, we investigate the potential of computer vision methods for scalable and early disease detection in plants. The advancement of vision-based plant disease identification is still significantly hampered by the lack of appropriate large-scale non-lab data sets. In light of this, we present Plant Doc, a dataset for identifying visual plant diseases. A total of 2,598 data points from 13 plant species and as many as 17 different disease categories are included in our collection. Annotating images taken from the internet scraped 300 hours of labour. Three models are produced for the task.

I.INTRODUCTION

India has a population that depends on agriculture to some extent—roughly 70%. Identification of plant diseases is essential for crop loss prevention. It is very challenging to manually inspect the plant illnesses. It takes a substantial amount of time, a significant amount of labour, and understanding of plant diseases. Image processing and machine learning models can be used to detect plant illnesses. Using pictures of the afflicted leaves, we have described a technique in this study for diagnosing plant illnesses. A subset of signal processing called visual processing can take important data or visual features and extract them. Machine learning, a part of artificial intelligence, automates tasks or provides guidance on how to complete them. The fundamental objective of machine learning is to comprehend the training data and incorporate it into models that should be beneficial to people. Consequently, given the large training data, it can assist in making sensible decisions and projecting the proper output.As classification criteria, leaf colour, leaf damage level, leaf area, and leaf texture are used. We have analysed numerous picture metrics or attributes in order to accurately detect different plant leaf diseases. In the past, experts could detect plant illnesses using chemical methods or a visual examination of the leaves. Artificial intelligence's machine learning component automates tasks or offers instructions on how to do them. Understanding the training data and incorporating it into models that should benefit people is the core goal of machine learning. Given the extensive training data, it can therefore help with decision-making and outcome projection.Leaf colour, leaf level of damage, leaf area, and leaf texture are utilised as classification criteria. In order to precisely identify various plant leaf diseases, we have examined a large number of photo metrics or features. In the past, scientists could identify plant diseases by looking at the leaves or by utilising chemical techniques.

II.LITERATURE REVIEW

The suggested strategy for identifying plant diseases employs statistical machine learning and image processing algorithms, which are computationally cheaper and require less time for prediction than current deep learning-based systems.BPNN, which is used for categorization, is used to find the plant disease. Shiroop Madiwalar and Medha Wyawahare investigated various image processing techniques for identifying plant diseases in their study. Authors looked into the ability to identify plant sickness using colour and textural attributes. They evaluated their algorithms using the dataset of 110 RGB images. The features obtained for classification included the GLCM features, the mean and standard deviation of the picture convolved with the Gabor filter, as well as the mean and standard deviation of the RGB and YCbCr channels. A support vector machine classifier was used for classification. According to the authors, GCLM features can be used to identify healthy leaves. While it is believed that colour characteristics and Gabor filter characteristics work best for identifying leaf spots and anthracnose-affected leaves, respectively. They achieved the highest accuracy of 83.34% using all the features gathered. Peyman Moghadam et al made a case for the use of hyperspectral imaging in the process of diagnosing plant diseases. The spectrums of the visible, near-infrared (VNIR), and short-wave infrared (SWIR) were used in this investigation. The k-means clustering method in the spectral domain was employed by the authors for the segmentation of leaves. They have introduced a novel grid removal algorithm with

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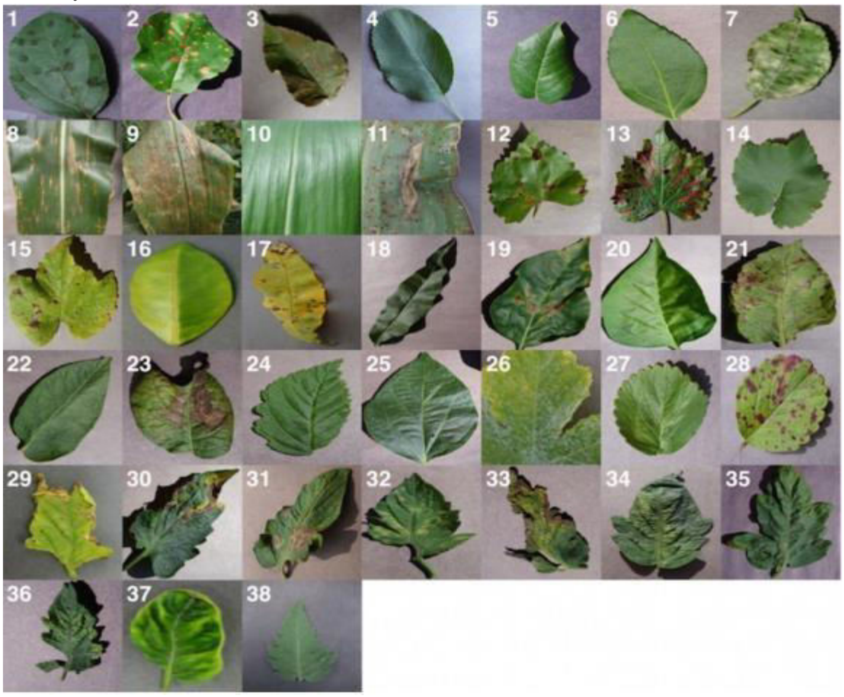
the aim of removing the grid from hyperspectral photos. In the VNIR spectral region, the authors' vegetation indicators were 83% accurate, and their entire spectrum was 93 percent accurate. By Sharath D. M. et al., the Bacterial Blight Detection System for Pomegranate Plant was developed. The authors divided the area of interest in the image using grab cut segmentation. Canny edge detector was used to extract the photo's edges. The authors have developed a method to predict the level of fruit infection with accuracy. Garima Shrestha et al. employed convolutional neural networks to pinpoint the plant disease. The authors successfully categorised 12 plant diseases with a classification accuracy of 88.80%. A collection of 3000 high resolution RGB photographs were used in the experiment. The network is composed of three blocks of convolutional and pooling layers. This raises the price of computing on the network.

III.METHODOLOGY

3.1 Set of data: For this experiment, Sharada P. Mohanty et al.'s Plant Village public dataset for plant leaf disease detection was employed. The dataset comprises of 87 000 RGB photos of healthy and diseased plant leaves, divided into 38 classes. We have only chosen 25 classes to test our method on.



Sample Images In Dataset

3.2 Data preprocessing and feature extraction: In any computer vision-based system, data preprocessing is a crucial effort. Prior to feature extraction, some background noise needs to be eliminated to obtain precise findings. As a result, the RGB image is first turned into a greyscale, and then the image is smoothed using a Gaussian filter. Otsu's thresholding algorithm is then used to the image to create binaries. To fill in the minor gaps in the foreground, the morphological transform is then performed to the binarized image. The RGB image of the segmented leaf is now obtained after the foreground has been detected using the bitwise AND operation on the binarized image and the original colour image. Shape, texture, and colour features are now extracted from the image following segmentation. The area and perimeter of a leaf are estimated using contours. The line that connects all of the spots along the margins of objects with the same colour or intensity is known as a contour. Each RGB channel's mean and standard deviation are also estimated. The image is first converted to HSV colour space, and the ratio of pixels with hue (H) channel pixel intensities between 30 and 70 and the total number of pixels in one channel is then calculated to determine the quantity of green colour in the image. Calculating the non-green portion of a picture involves removing the green component from 1.

3.3 Feature selection: It is a crucial phase in all machine learning issues. In this project, features are chosen based on the variables' correlations with the target variable. The feature green part of the leaf (F1) and the green part of the leaf (F2) have a very high correlation (1), indicating that both variables are interdependent. Therefore, we eliminated one of them (F2). Less correlated features, such as the green channel mean, red channel standard deviation, blue

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channel standard deviation, dissimilarity (f5), and correlation (f8), would not have a significant impact on the construction of the model for apple disease prediction. Therefore, we also dropped these variables. The data is now processed to machine learning classifiers to detect the patterns in the data after feature selection.

3.4 Classification Algorithm: For classification or detection tasks, the random forest classifier has been utilised. It is a component of ensemble learning in which several base estimators are used to forecast the output [8]. Typically, decision trees are employed to gain improved accuracy. However, they are vulnerable to overfitting issues. Therefore, a random forest classifier—a collection of many decision trees—is employed to address this problem. Each tree is trained using various subsets of the entire dataset, which might lessen overfitting and increase the classifier's accuracy. The dataset was divided into a train set (80%) for model fitting and a test set (20%) for model validation. The K-fold cross validation method is used to calculate the accuracy score. With no bias, this approach can determine accuracy throughout the entire dataset. After the data has been fitted, the f1 score, precision, recall, and accuracy have been computed from the test data to analyse the model's performance. For the analysis of false positives and false negatives, the ROC curve and confusion matrix were plotted.

FACILITIES REQUIRED FOR PROPOSED WORK

1) Software: Python (programming language).
Any operating system (windows, Linux, ubuntu).
2) Hardware:
1 GHz or faster Pentium class PC.
A minimum of 2 GB of RAM and a minimum of 1 GB of free disk space is also required. Arduino Mega controller, Raspberry Pi microcontroller. OV 7670 camera module.

IV.APPLICATIONS

We were able to adapt the above solution to a mobile environment by using models that very significantly reduce complexity, without sacrificing the effective accuracy. This allowed us to achieve the best possible performance, given that the application should predict the bounding boxes and classes in real time in a mobile CPU. We have built application that utilizes Mobile Nets Object Detection Network due to its efficiency and competitive accuracy. The network builds on top of the SSD framework.

V.CONCLUSION

We have successfully developed a computer vision-based system for plant disease detection with average 93% accuracy and 0.93 F1 score. Also, the proposed system is computationally efficient because of the use of statistical image processing and machine learning model.

REFERENCES

1) S. D. Khirade and A. B. Patil, "Plant Disease Detection Using Image Processing," 2015 International Conference on Computing Communication Control and Automation, 2015, pp. 768-771, doi: 10.1109/ICCUBEA.2015.153.
2) S. D. Khirade and A. B. Patil, "Plant Disease Detection Using Image Processing," 2015 International Conference on Computing Communication Control and Automation, 2015, pp. 768-771, doi: 10.1109/ICCUBEA.2015.153..
3) P. Moghadam, D. Ward, E. Goan, S. Jayawardena, P. Sikka and E. Hernandez, "Plant Disease Detection Using Hyperspectral Imaging," 2017 International Conference on Digital Image Computing: Techniques and Applications (DICTA), 2017, pp. 1-8, doi: 10.1109/DICTA.2017.8227476.
4) S. D.M., Akhilesh, S. A. Kumar, R. M.G. and P. C., "Image based Plant Disease Detection in Pomegranate Plant for Bacterial Blight," 2019 International Conference on Communication and Signal Processing (ICCSP), 2019, pp. 06450649, doi: 10.1109/ICCSP.2019.8698007..
5) 10.1109/ICCSP.2019.8698007. 5. G. Shrestha, Deepsikha, M. Das and N. Dey, "Plant Disease Detection Using CNN," 2020 IEEE Applied Signal Processing Conference (ASPCON), 2020, pp. 109-113, doi: 10.1109/ASPCON49795.2020.9276722.
6) Breiman, L. Random Forests. Machine Learning 45, 5–32 (2001). https://doi.org/10.1023/A:1010933404324.