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Crop Disease Identification Using Computer Vision And Machine Learning Techniques

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Abstract

The paper examines various classification methods dedicated to the identification various illnesses of plants, emphasizing the crucial role of early detection in preserving crop quality and yield. It delves into different approaches, including image processing, machine learning, artificial neural networks, and, more prominently, deep learning. With a focus on emerging methods for in-depth comprehension, the review provides a detailed analysis starting from traditional machine learning methods. It outlines the targeted crop diseases, the utilized models, data sources, and performance metrics employed across studies for disease identification. The review highlights deep learning's superior accuracy compared to traditional methods and identifies important elements that have an influence its performance. By documenting these approaches, the paper aims to enhance accuracy and reduce response time in plant disease identification, with specific attention given to efforts in diagnosing diseases in Indian agricultural settings using authentic datasets.

I. Introduction

Plants are indispensable for the economy and mitigating climate change. With global recognition of climate change as a pressing issue, countries like Pakistan are engaged in tree-planting initiatives to maintain ecological balance. The extinction of plants due to industrial operations is linked to ozone layer depletion and global warming. Climate change forecasts predict a future change rate far exceeding historical warming rates. Moreover, plants are crucial in the food industry, where ensuring global production balance is a significant challenge. Additionally, plants play an important role in healthcare but can suffer from various diseases. Economically, losses in food, fiber, and ornamental production due to plant pests and diseases are estimated to be in the hundreds of billions annually. Given their essential role in human survival, global concern for plant conservation and protection is paramount. Common symptoms of plant diseases include leaf rust, stem rust, sclerotinia, powdery mildew, anthracnose, phytophthora, septoria brown spot, and chlorosis. Traditionally, experts identify plant diseases by examining the physical condition of leaves, stems, or fruits, requiring significant human resources. [1]

However, in today's era of technology and automation, this approach is deemed inefficient. There is a growing interest in developing automated systems to diagnose plant diseases. Numerous investigations have explored this using traditional machine learning methods. This study aims to create an automated system for plant disease detection using deep learning techniques, a subset of machine learning.[2]

Deep learning offers advantages Unlike traditional machine learning since feature engineering and domain expertise are no longer required. Instead, deep learning algorithms, similar to CNNs, or Convolutional Neural Networks,able to automatically extract characteristics from images.CNNs are highly proficient in extracting visual features..[3]

The proposed system, known as a plant disease detector, utilizes CNNs to examine plant photos leaves to identify illnesses. By utilizing in order to teach the network a large collection of pictures showing both both well and ill plants, The example can learn to precisely categorize the kind of disease present in plant leaves. This automated approach possesses the capacity to revolutionize diagnosisas well as controlling plant illnesses. [4]

As deep learning (DL) architectures continued to advance, researchers began applying them to various agricultural applications, particularly in image recognition and classification. In one study, leaf classification was conducted using a modified CNN and Random Forest (RF) classifier across 32 plant species, achieving a classification accuracy (CA) of 97.3%. Nevertheless, this strategy was less successful. in detecting occluded objects. Other applications included leaf and fruit counting using deep CNNs, additionally crop type classification utilizing modified CNNs, VGG 16, LSTM units, and CNN combined with RGB histogram techniques. Performance evaluation metrics varied across studies, including CA, Intersection over Union (IoU), and F1-score. Several researches failed to report training/validation accuracy and loss. Furthermore, DLtechniques have been used for plant recognition tasks, employing modified CNNs and AlexNet architecture, and evaluated primarily based on CA. [5]

This article introduces a cutting-edge deep convolution neural network (DCNN) model created to diagnose 42 ailments of the leaves spanning 16 plant species. The research incorporates

Fig. 1. Rusted leaf

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 223, 223, 32)      896

 max_pooling2d (MaxPooling2  (None, 111, 111, 32)      0
 D)

 conv2d_1 (Conv2D)           (None, 109, 109, 64)      18496

 max_pooling2d_1 (MaxPoolin  (None, 54, 54, 64)        0
 g2D)

 flatten (Flatten)           (None, 186624)            0

 dense (Dense)               (None, 64)                11944000

 dense_1 (Dense)             (None, 3)                 195

=================================================================
Total params: 11963587 (45.64 MB)
Trainable params: 11963587 (45.64 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
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Fig. 2. convolutional Neural Network Model

employing strategies for hyperparameter optimization and data augmentation to improve the disease's performance detection model. Various techniques, including BIM, DCGAN, and NST, are employed to generate augmented leaf photographs. The DCNN architecture is trained using a dataset comprising 58 classes of diseased and intact plant leaves. Hyperparameter optimization is conducted using arbitrary searching using a coarse-to-fine technique to optimize the most common hyper-parameters. [6]

The feature-building procedure extraction is feature extraction. from the image to construct feature vectors, which can be statistical, structural, or signal processing-based. As an illustration, Moments of color are utilized for extracting color statistics (Semary et al., 2015), while a combination of Gabor Transform (GT) and Wavelet Transform (WT) is employed (GWT) for the extraction of multiscale features (Prasad et al., 2016). [7]

II. Literature Survey

In their paper titled "Deep Learning for Image-Based Plant Detection" , Prasanna Mohanty et al. propose an approach for detecting plant diseases by training a convolutional neural network (CNN). The CNN framework is trained to distinguish between healthy and infected plants across 14 different species. Remarkably, the model achieves an exceptional accuracy of 99.35% on the test dataset. [8]

However, when applied to images obtained from reputable from online sources, the model's accuracy drops to 31.4%. While this performance is superior to random selection, it indicates the requirement for a more diverse training dataset to enhance accuracy. Additionally, exploring variations of the model or neural network training methods may lead to further improvements in accuracy. These findings suggest opportunities to make plant disease diagnosis more accessible to a broader audience.

Fig. 3. Trained Crop Image

The suggested survey article provides an overview and synthesis of contemporary Capsule Network designs and implementations. Following the introduction of deep learning methods, the arduous task of feature engineering, which often led to high dimensionality, has been significantly alleviated. Whiledeep learning models Convolutional Neural Networks (CNNs), for example have shown promise, Usually, they require substantial amounts of data and computational resources. Capsules were developed in order to deal with some of the limitations encountered by CNNs, and they have demonstrated effectiveness thus far. [9]

This article delves into the current state of Capsule Networks, offering insights into existing designs and implementations. By exploring the advantages and disadvantages of

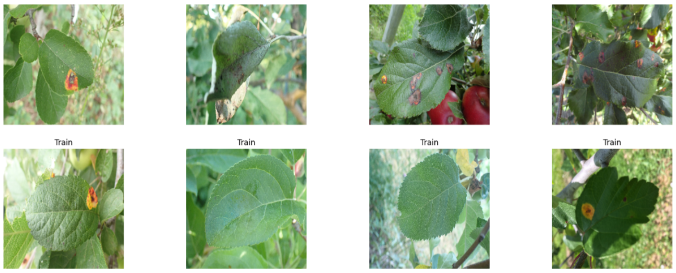

Fig. 4. Images used for Training the data

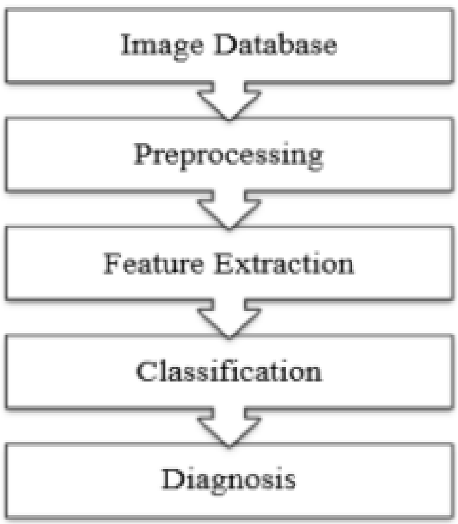

Fig. 5. Proposed Model Flowchart

CapsNets, the computer vision community aims to develop robust machine vision algorithms through continued research in this domain.

III. Methodology

Deep Learning involves a comprehensive review of relevant literature and analysis within the realm of Identification and categorization of plant diseases. Initially, a keyword-based search was conducted across scientific databases such as IEEE Xplore, Science Direct, and Google Scholar, using terms like deep learning, plant disease identification, and plant disease classification to identify pertinent research papers. Subsequently, a selection process was undertaken to choose papers that specifically addressed machine learning and deep learning methods for treating plant diseases identification.[10]

Each selected paper was individually analyzed, taking into account related citations and investigating particular research questions concerning the crop disease problems tackled, models utilized, types of data employed, pre-processing techniques applied, and the performance levels achieved. This methodical approach enabled for a detailed examination of The efficaciousnesss of the techniques utilized in the selected papers,

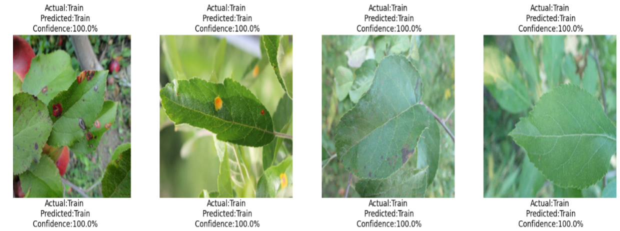

Fig. 6. Predicted and Actual Images

shedding light on trends, challenges, and prospective avenues for the field's continued development of agricultural disease diagnosis. Additionally, the document outlines fundamental steps for plant illness identification, encompassing image acquisition, preprocessing steps like cropping and resizing, machine learning for feature extraction and categorization models, providing a structured framework for disease identification studies conducted in the agricultural domain. [11]

Data preprocessing plays a vital part in computer vision solutions. To ensure accurate results, it's essential to eliminate background noise before feature extraction. Initially, the RGB image is converted to grayscale, subsequently the application of a Gaussian blur filter for image smoothing. Subsequently, Otsu's thresholding An algorithm is employed. to binarize the image. A morphological transform is then applied to close small holes in the foreground of the image. [4]

After foreground detection, a bitwise AND operation is performed between the binarized image and the original color image to obtain an RGB image of the segmented leaf picture. Following image segmentation, characteristics like shape, texture, and color are extracted. Contours are employed to compute the leaf's area and perimeter, representing lines that connect points along object edges with similar color or intensity.

Additionally, the standard deviation and average of every RGB channel are calculated. To evaluate the quantity of green color present, the image is converted to the HSV color space, and the proportion of pixels with a hue (H) channel intensity between 30 and 70to the total quantity of pixels in that channel is computed. The non-green portion of the image is obtained by subtracting the green color information. [12]

IV. Conclusion

The 14-layer Model of deep convolutional neural network consists of five convolutional layers paired with five max-pooling layers. To optimize hyperparameters, a a random search using a coarse-to-fine technique was applied. The training of the model was done with 139,000 pictures for both instructional and validation datasets, achieving impressive classification Recall, accuracy, precision, and F1 score on the training data. Notably, the optimization of hyperparameters and strategies for augmentation of data significantly impacted the model's performance. Compared to traditional transfer learning methods, the 14-layerModel of deep convolutional neural network model demonstrated superior classification performance. Future research aims to expand the dataset with novel categories of plant illnesses as well as more training images, alongside enhancing the DCNN architecture with additionalconvolutional layers and supplementary layers. Additionally, there are plans to explore the potential of profound understanding methodologies in estimating disease probability and analyzing disease severity.

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