

Real Time Plant Disease Detection Model using Deep Learning

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Abstract— Convolutional neural networks (CNNs) have had remarkable success in classifying a variety of plant diseases through deep learning. However, just a few researches have shed light on the inference process, leaving it as an unsolvable mystery. In addition to guaranteeing the learnt feature's dependability, revealing the CNN to extract it in an understandable form enables human intervention-based verification of the model's veracity and the training dataset. Using a CNN that had been trained using a publically accessible collection of images depicting plant diseases, several neuron-wise and layer-wise visualisation techniques were used in this study. We demonstrated that neural networks can, when diagnosing an illness, capture the hues and textures of lesions particular to that disease, which is similar to human judgement. The most critical aspect of agriculture is striking a balance between produce and population. Due to a variety of issues, including natural disasters, unforeseen rainfall, nutrient deficiencies in the soil, etc., the majority of farmers failed to produce and balance the crops. The main issue, however, is pest infection, which is the root of all the issues. To learn about plant diseases, several researchers employed a variety of methods. Convolutional neural network-based deep learning techniques are frequently utilised to solve image-oriented problems. A powerful and successful method for image analysis is the CNN (ConvNet) neural network model of deep learning. In this study, various models for plant disease detection with CNN are compared. The research report concludes by summarising its findings, identifying its limitations, and making recommendations for classification

Keywords— *machine learning, deep learning, image processing, classification*

I. INTRODUCTION

Food security is seriously threatened by crop diseases, but because many regions of the world lack the requisite infrastructure, it is still difficult to identify them quickly. Smartphone-assisted disease diagnosis has been made possible by deep learning, rising smartphone adoption globally, and recent developments in computer vision. We train a deep convolutional neural network to recognise 14

crop species and 26 diseases using a public dataset of 54,306 photographs of sick and healthy plant leaves collected in controlled settings (or absence thereof). The trained model's 99.35% accuracy on a held-out test set serves as proof that this approach is effective. Utilizing big image datasets that are made publically available, deep learning models are constructed. A major danger to food security for a long time has been plant diseases [1-2], which severely reduce agricultural output and crop quality. It has shown to be quite challenging to diagnose diseases with accuracy and precision. Historically, visual examination and human annotation have been the primary methods for identifying plant diseases [3-4].

Visual illness detection is more difficult, less accurate, and only possible in a few locations. In contrast, using an automatic detection method will require fewer efforts, less time, and provide more accurate results. The method of evaluating a disease's afflicted region and figuring out how the colour of the affected area differs is called image processing [5-7]. Texture and other qualities are also employed quantitatively in paper [5]. K-means algorithm and thresholding values are employed in paper [6] colour based feature for segmentation and identification.

We contrast visualisation methods to CNNs in the applications of plant science in this study based on the findings of the other studies. Our results show the efficacy of various visualisation methods and show that the CNN is capable of capturing the lesion-specific features of different diseases. The [8] CNN architecture and dataset changes, however, necessitate specific layer adjustment for many algorithms in order to get the best results. By lowering the amount of network parameters by 95%, we also identify the appropriate number of feature extraction layers based on the layer-wise visualisation. The study's contributions are listed in the following order. First of all, this work is the first to attempt a comprehensive analysis of the data collected by CNNs during the detection of plant illnesses. This issue has a

considerable negative impact on the quick growth of deep learning approaches in plant characterization tasks. In order to choose and evaluate CNN models for processing plant images, it establishes a benchmark. From a computer science perspective, the visualisation of a CNN [9] utilised in this study for processing plant images produces unique results as well. The trajectory of the visualisations differs substantially from past discussions in visualisation studies for general object recognition.

II. BACKGROUND

Population pressure is one of the most important variables influencing Indian agriculture because 70% of the population depends directly or indirectly on farmers for their food. The production of agricultural goods is directly impacted by a number of problems, including a lack of scientific methodology and incorrect knowledge of fertilisers, insecticides, and pesticides [10]. The graph below, which highlights the existence of population pressure, displays year-over-year consumption in relation to productions in tonnes [11-12]. From a farmer's perspective, the most important step in the agricultural field is the early diagnosis of plant infection. The bulk of plant illnesses are analysed primarily on the basis of the plant's leaves. It is advised to employ computer vision for disease detection in the early stages of the plant life cycle. Several scholars have employed a variety of procedures and strategies with the usage of traditional image processing tools. In particular, The afflicted area of the plant will be identified in the future image processing milestone using convolutional neural network models that have been built and have attained the required accuracy rate in the findings. shown by hyperspectral imaging how to identify plant diseases [13]. Both the VNIR (visible and near-infrared) and SWIR (short-wave infrared) spectrums were used in this study. The scientists were able to separate leaves by using the k-means clustering algorithm in the spectral domain. To get rid of the grid in hyperspectral photos, they have introduced a revolutionary grid removal technique.

Using the full spectrum, the authors' accuracy was 93%; using vegetation markers in the VNIR spectral range, their accuracy was 83%. The suggested approach produced more accurate results; however it is too expensive because it requires a hyperspectral camera with 324 spectral bands [14-15]. Because of their powerful computational capabilities, crystal-clear screens, and full built-in accessory sets, including high-definition cameras, smartphones in particular offer highly inventive ways to assist with disease detection. By 2025, there will likely be 5 to 6 billion mobile phones in use worldwide. 69% of the world's population had access to mobile broadband at the end of the year, a 12-fold increase over mobile broadband penetration in 2015. The combination of high-definition cameras, high-performance mobile processors, and widespread smartphone penetration may, if theoretically achievable, enable disease diagnosis based on automatic picture identification to be made available at a

never-before-seen scale. This proves the viability of the technology.

In Paper [16], the methodologies for classifying and identifying plant leaf diseases are discussed. Preprocessing is followed in this case by feature extraction. RGB shots are first made white, then they are converted to grey level images, which may be used to extract the vein image from each leaf. The image is subsequently subjected to basic morphological processes. A binary image is then created from the original image. The value of a binary pixel is then, if it is 0, converted to the suitable RGB image value. Last but not least, a naive Bayesian classifier, a dominating feature set, and Pearson correlation are used to determine the presence of a disease.

III. MATERIAL AND METHODS

The image processing concept is used to perform some operations on digital images that enable to find the solution for image related problems. Image processing consists of a series of phases that is, Acquisition of Images, Pre-processing of Images, Segmenting images, Finding features, Discovery & Classification.

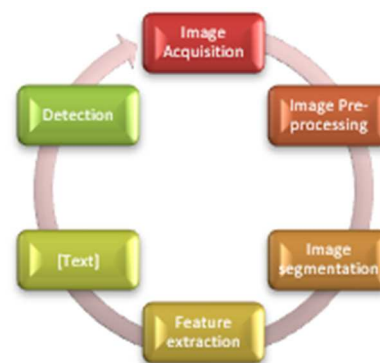


Figure 1. Phases of Image processing

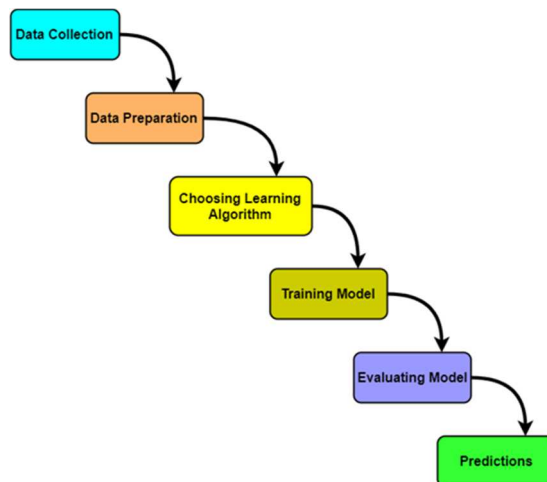


Figure 2. Proposed method

CNN of deep learning used to perform computer vision on an image and video recognition. CNN is advanced than ANN, this Neural Network Model is used in image

recognition and classification. CNN works on pixel of images, then train the model for extracting the features for better classification [17]. In a CNN's tiers, there are; , Layer of input, Layers of output, Layered cover that has, There are numerous convolutional layers, layer pools,all-encompassing layers, an adjustment layer.

The structure of a convolutional neural network is shown in the diagram below.

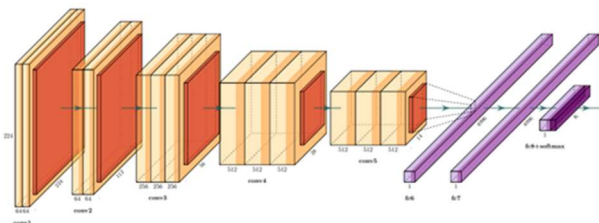


Figure 3. CNN

A. Summary of the Dataset

We analyse 34,788 photos of plant leaves that have been categorised under 38 different themes. We attempt to forecast the crop-disease association for each class label using only the visual characteristics of the plant leaf. Each class label identifies a pair of diseases and crops. For each crop-disease association in the PlantVillage dataset, an example is shown in Figure 1. We downscale the images in all of the research's methods to 256 *256 pixels, then we optimise the models and give predictions using these smaller versions of the photos.

B. Data Augmentation Phase

The information by adding copies of existing photos that have been slightly altered, the augmentation step is utilised to expand the dataset. Crop, Scale, Flip, Rotation, Translation, Sizing, and Gaussian Noise are common augmentation methods. Image pre-processing is typically advised to remove undesired parts and improve the image for future processing [18]. For AlexNet, CNN's input layer allows images with the following dimensions: 227 x 227; 224 x 224; for other architectures like DenseNet, ResNet, and VGG[3].

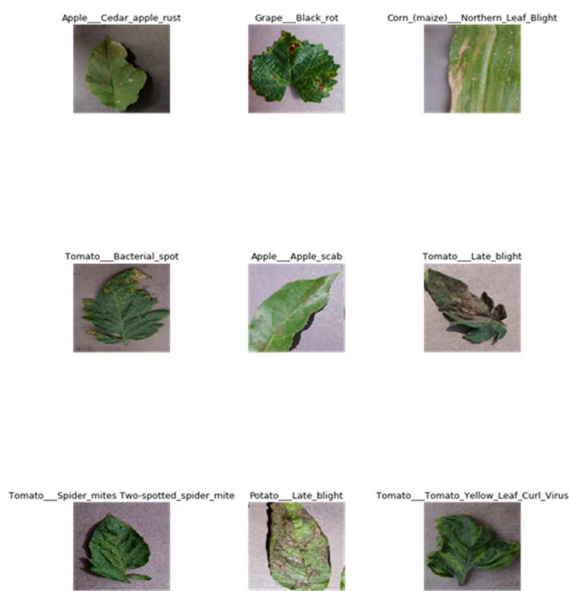
C. Data Detection and Classification Phase

This stage discussed the identification and categorization of plant diseases using just a few CNN image classification architectures., the following table contrasts various CNN models that were employed to find plant diseases. We were able to view the learned features and extract the hidden layer output using one of the more time-consuming methods [6] by feeding a photo to the CNN and stopping the calculation at the layer of interest. Since our network uses the rectified linear unit (ReLU) activation function, a feature extraction layer only passes positive values to the succeeding layer, the answer to the question "What part of the image was important for the inference?" can be roughly implemented by simply

visualising the intermediate outputs [10]. Even though each layer's output was produced using the same process, the earlier research [6] mostly focused on the outcomes of the first convolutional layer.

IV. RESULT AND DISCUSSION

Every machine learning operation must begin with the feature selection process. When picking features for this project, the relationships between the variables and the target variable are taken into account. For the apple dataset, Fig. shows the correlation between each variable and each other. 3. It is clear that the two variables are interdependent based on the highly significant correlation (1) between the green leaf features (F1 and (F2)). We lost one of them as a result (F2). Less correlated qualities, such as the mean of the green channel, the standard deviation of the red channel, the standard deviation of the blue channel, the dissimilarity (f5), and the correlation, won't have a significant impact on the creation of the model for the prediction of apple disease (f8). As Following feature selection, the data as shown in Figure 4.



Phase 4. Dataset Sample

In order to compare how well each of these designs performed on the PlantVillage dataset, we either completely built the model in one case or modified previously taught models in the other (trained on the ImageNet dataset). Transfer learning was made easier in the Google Neural Network and AlexNet's fc8 layer by setting the weights of the loss 1, 2, and 3/classifier layers to zero. In contrast to transfer learning, we do not restrict any layer's learning when we train the model. In other words, the starting condition of the weights of a few layers facilitates the ability to distinguish between these two learning processes. After that, the accumulated data are normalised. The procedure used to normalise the data is described below: [19-20].

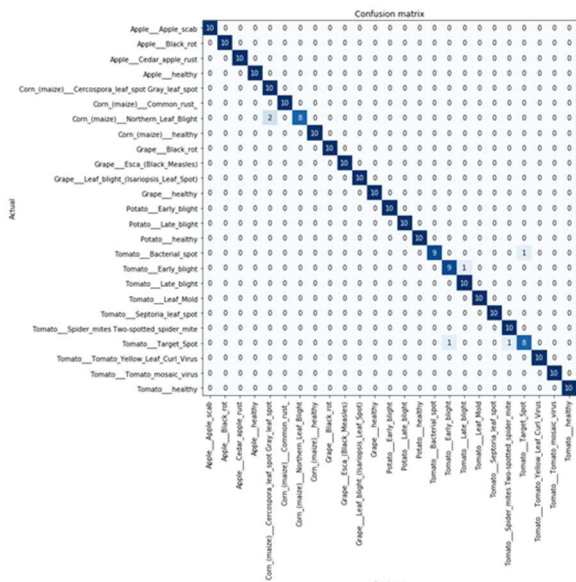


Figure 5. Confusion matrix

The first thing we want to draw attention to is the fact that random guessing frequently only achieves an overall accuracy of 2.63% on a dataset with 38 class labels. The overall accuracy we were able to achieve on the PlantVillage dataset was between 85.53% in each of our testing setups, which included three visual representations of the picture data. This demonstrates the deep learning method's strong suit for comparable prediction challenges (see Figure 6). It shows the average F1 score, recall, precision, and accuracy for each of our trial combinations. After the first fall in learning rate, the experimental settings converge in almost all situations. Each experimental setup is run for 30 epochs in total.

$$\text{Normalized cost} = (x_i - \min(x)) / (\max(x) - \min(x)) \tag{1}$$

The following method changed into used to generate the attitudelon—23 features.

The layer that makes visualization easier should be chosen in fact. Even the explanation map, designed for the lesion detection of plant diseases, strangely displays attributes that are different from those in the original literature due to modifications in the network design and dataset. Therefore, we suggested visualizing each layer to ascertain which layer would be most useful for visualization. The findings show that Grad-CAM and the explanation map produce layer-wise attention maps that emphasise lesions with extraordinary specificity (Figure 6). Of the procedures that have been studied, they are without a doubt the most affordable. Grad-CAM requires fewer calculations than other gradient-based methods since it evaluates the gradient of the intermediate map in respect to the inference result.

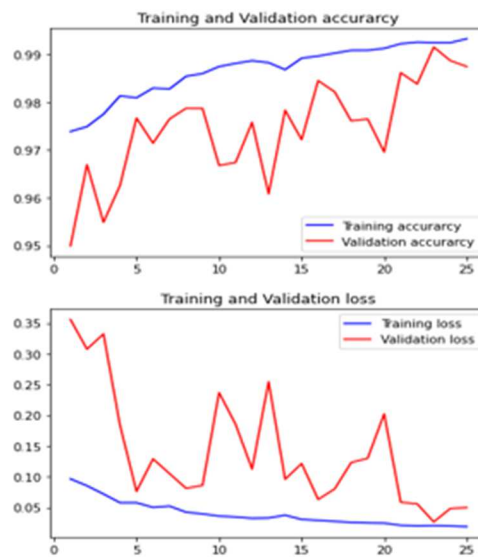


Figure 6. Accuracy plot

The accuracy rate of different models of the CNN architectures visualized using below chart.

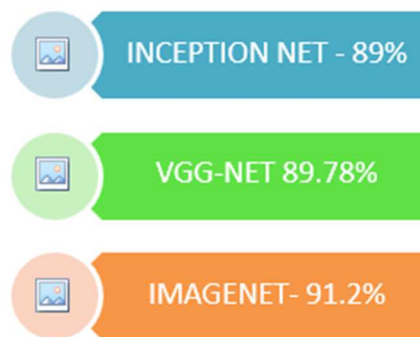


Figure 7. Model comparison

The most obvious lesions in each image were emphasised when the visualisation techniques were compared. One can compare the specificity and sensitivity of various approaches using qualitative measures by combining datasets with annotation labels for particular regions of the lesions, which are frequently prepared for semantic segmentation tasks. CNN might choose to concentrate on surprising subjects, though. To prevent overfitting or dataset bias, it is imperative to investigate whether these characteristics have physiological relevance.

V. CONCLUSION

The algorithm used for image segmentation, which is used to automatically identify and classify plant leaf diseases, is described below. It is possible to identify plant leaf diseases by using the review of several disease categorization methods provided in this study. The algorithms and techniques were tested on a variety of species, including okra, grape, paddy, and jute. In order to examine the samples, associated plant diseases were acquired. The best outcomes are obtained with

the least amount of computational work, which demonstrates the algorithm's effectiveness in locating and classifying leaf diseases. The capacity to identify plant ailments early on is another advantage of adopting these techniques. With artificial neural networks, data is categorized to increase recognition rates.

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