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Plant breeding

FRUIT DISEASE CLASSIFICATION AND LOCALIZATION USING REGION BASED REGRESSION

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Abstract

Fruit disease classification using computer vision techniques is completely viral upon machine learning capabilities. The complete analysis is based upon regression using region proposal networks and their optimization using Gradient Clipping methodology. Fruit diseases such as flyspeck, blotch, scab and rot are detected and classified using the Region proposal network regression. The recent works carried out on the fruit disease detection and classification on agricultural crops were gathered and surveyed in this paper. Finally the very recent work carried out using regression and computer vision techniques were identified and applied to the data collected here with 6231 images and 24 classes. The diseased and disinfected were filtered for training purpose into 3110 images as diseases and the rest as disinfected. The hyperparameters tuning optimization was able to fit only the random data images, instead gradient clipping resulted in the proper limit cropping of the diseased portions of the crop footage. To improve the training data stability regression was employed with this optimization to show the results obtained from 95.3% to 97.8%. Here, the RCNN classification using neural networks resulted in the overall accuracy of the fruit disease classification model to 95.83%, where the Gradient Clipping optimization resulted in the improvement of accuracy of model to 97.8%.

Key words: classification, prediction, region proposal, regression, CNN, deep learning

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1. Introduction. Fruit disease classification involves identifying and categorizing different diseases that can affect fruit crops. This is an important task in agriculture because it allows farmers to monitor their crops and take appropriate action to minimize the spread of disease and reduce crop losses. There are several approaches to fruit disease classification, including traditional visual inspection, laboratory testing, and machine learning algorithms. Machine learning algorithms, in particular, have gained popularity in recent years because they can analyze large amounts of data quickly and accurately, and can be trained to identify subtle patterns that may not be visible to the human eye. By implementing a fruit disease classification system, farmers can quickly identify and respond to potential disease outbreaks, preventing crop losses and ensuring the quality of their produce. Fruit disease classification involves identifying and categorizing different diseases that can affect fruit crops. This is an important task in agriculture because it allows farmers to monitor their crops and take appropriate action to prevent the spread of disease and minimize crop losses. There are several fruit disease classification algorithms that can be used to identify and categorize different diseases that can affect fruit crops. Some commonly used algorithms are: Convolutional Neural Networks (CNNs). CNNs are deep learning algorithms that are widely used for image classification. They work by using multiple layers of convolutional filters to extract features from images, which are then used to classify the images into different classes.

2. Related works. Many fruit disease classifier models were constructed by using the CNN algorithm and the list of results obtained are given below.

1. In the study of Khattak et al. [1] published in the Journal of Agricultural Science and Technology, researchers used a CNN to classify citrus fruit diseases. The overall accuracy 92.6% on a dataset of 3200 images was achieved by this model.
2. In the study of Uttam [3] the author used CNN to classify grapevine diseases [3]. The overall accuracy of 98.3% on a dataset of 4062 images was achieved by the model.
3. The study of Khan et al. [6] used a CNN to classify banana diseases. The model achieved an overall accuracy of 99.1% on a dataset of 2400 images.
4. In the study of Sun et al. [8] researchers used a CNN to classify apple diseases. The model achieved an overall accuracy of 98.6% on a dataset of 1876 images.

3. Design of R-CNN algorithm. Fruit disease classification using R-CNN [9] can be done using a sim ilar approach for object detection. Here are the steps involved:

1. Collect and preprocess the dataset: First, we need to collect a dataset of images of fruits with and without disease. We also need to annotate the images to identify the location of the fruits and their corresponding labels (i.e. diseased or healthy). Preprocessing steps may include resizing, cropping [10], and normalizing the images.

2. Train a region proposal network (RPN): Next, we need to train an RPN [11] to propose regions of interest (ROIs) in the image that are likely to contain fruit. The RPN can be trained using a subset of the dataset with only the fruit images.
3. Extract features from the ROIs [12]: Once the ROIs are identified, we need to extract features from the corresponding regions of the image using a CNN. This CNN can be pre-trained on a large dataset like ImageNet to learn general features, or it can be trained from scratch on the fruit disease dataset.
4. Classify the ROIs: Using the extracted features, we can classify each ROI as either diseased or healthy using a classification layer on top of the CNN. This can be done using techniques like softmax or logistic regression.
5. Non-maximum suppression: Finally, we need to apply non-maximum suppression (NMS) to remove overlapping bounding boxes and keep only the most confident predictions.

Consisting of 820 images of apples and 610 images of guavas with a random input of images the training and testing sets are formed for training the model and evaluating the model and those images were labelled using the CNN and the convolution layer of dimensions $256 \times 3 \times 3$. The labelled data folder is taken into the training data of R-CNN. ROI (Regions of Interest) layers are constructed using the 7×7 matrices of Keras. Refining bounding box positions is an important step in object detection tasks, including fruit disease classification.

3.1. Region proposal networks. In Region-based Convolutional Neural Networks (R-CNN), bounding boxes are used to identify regions of interest (ROIs) in an image that is likely to contain objects of interest, such as fruit or fruit diseases as shown in Fig. 1. Here is how bounding boxes are used in the R-CNN pipeline:

- Region Proposals: The first step in the R-CNN pipeline is to generate a set of region proposals, each of which is a bounding box that encloses a region of the image that may contain an object of interest. There are several algorithms that can be used for region proposal, such as Selective Search or EdgeBoxes.
- CNN Feature Extraction: For each region proposal, a feature vector is extracted using a convolutional neural network (CNN). The CNN is pre-trained on a large dataset, such as ImageNet, to learn general features that are useful for image classification tasks.
- Classification and Refinement: The feature vector for each region proposal is fed into a set of fully connected layers that are trained to classify the region proposal as containing an object of interest or not. The output of the classification layer is a probability score that indicates the likelihood of the region proposal containing an object of interest. The bounding box coordinates for the region proposal are also refined based on the features learned by the CNN.

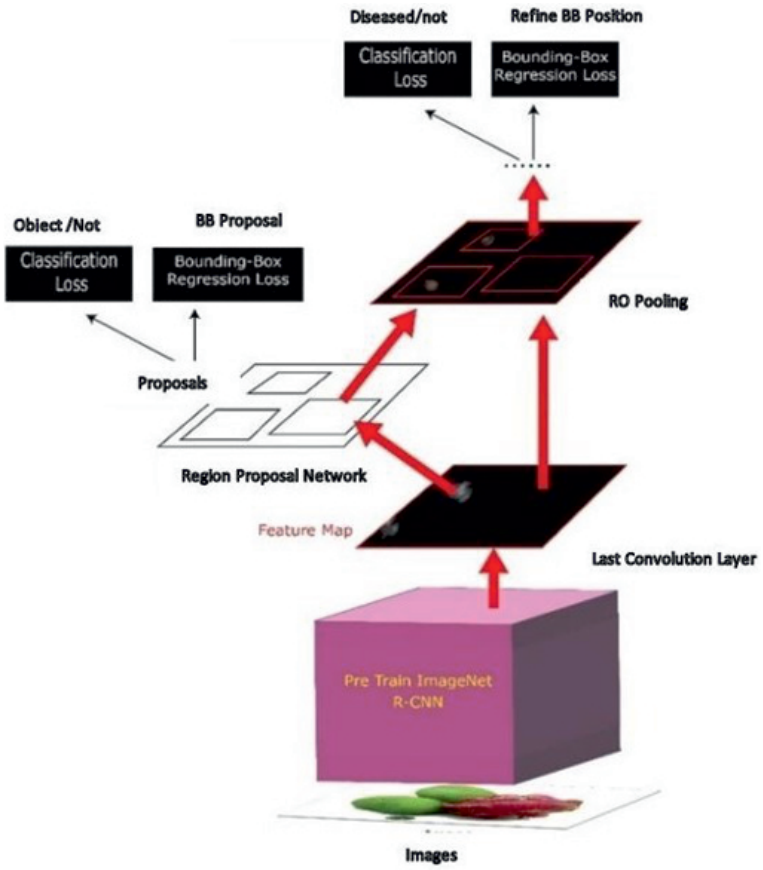


Fig. 1. The coordinator plane of RGL

- Non-Maximum Suppression (NMS): To eliminate redundant bounding boxes and select the most accurate bounding boxes for each object, non-maximum suppression (NMS) is applied. This involves comparing the probability scores and bounding box coordinates for all region proposals and keeping only the ones with the highest scores and non-overlapping bounding boxes.
- Output: The final output of the R-CNN pipeline is a set of bounding boxes that enclose objects of interest in the image, along with their corresponding class labels and probability scores.

RPN begins with a backbone network, such as VGG or ResNet that is used to extract features from the input image. The features map with dimensions $5 \times 7 \times 7$ produced by the backbone network is then passed through the Region Proposal Network, which is responsible for generating a set of region proposals.

3.2. Classification results. In this section, the constructed classification model accuracy and loss during training and validation is evaluated across the random input images. Up to Epochs = 60, iterations are repeated and the summary

of Region classifications are represented through the image results given below. To address overfitting and improve the model's generalization performance, you can try using techniques such as regularization, data augmentation, or early stopping during training. Regularization methods such as L1 or L2 regularization can help prevent the model from becoming too specialized to the training data. Data augmentation techniques such as flipping, rotating, or scaling the images can help increase the diversity of the training data and improve the model's ability to generalize. Early stopping can prevent the model from overfitting by stopping the training process before the model starts to memorize the training data.

Figure 2 shows the classification accuracy and loss recorded by simulating the R-CNN classification model. Softmax is used as the threshold to adjust the hyperparameters of the training mode with the parameter alpha (α). Equation (1) derived from [10] shows the parameter α with the equivalent parameters as follows:

$$\alpha_i(Z) = \frac{\exp(Z_i)}{\sum_{j=1}^{m} \exp(Z_j)}, \quad i = 1, \ldots, m, \tag{1}$$

where $\alpha_i(Z)$ is the output of fully connected layer, Z_i is the output of the layer i, and m is the number of classes.

This expression is used for calculating the estimator probability yield for various object classes. Loss percentage is reduced to 0.30 for validation loss and 0.20 for testing set.

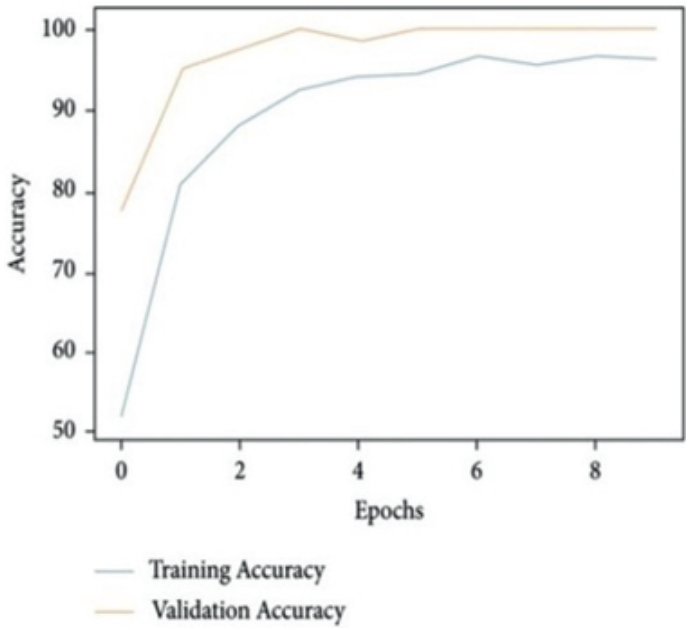


Fig. 2. R-CNN fruit disease classification accuracy

Table 1

Accuracy and loss observed under model optimization

Estimator	Accuracy	Loss	Epochs	Threshold
SoftMax1	95.83	0.15	140	1.6
SoftMax2	100	0.20	100	0.5
SoftMax3	99.84	0.30	50	0.27
SoftMax4	97.8	0.47	15	0.17

Table 2

F1 Scores of each fruit classified

Fruits	Accuracy	F1 Scores	Precision	Recall
Red Apples	92	0.91	94	93
Green Apples	99.2	1	96	95
Grapefruits	98.7	0.95	94.7	92.8
Guava	97.4	0.86	94	93

Tables 1 and 2 represent the accuracy and loss of each model on different samples in the data set.

4. Conclusions. NN with threshold Gradient Clipping methodology shows the optimal accuracy of 97.8% as the overall model accuracy after performing gradient clipping on the Softmax estimator layer and 95.63% of accuracy before applying threshold and gradient clipping are statistically estimated by the loss and number of epochs. Loss estimation is also optimized which is required by the model target achievement. The results are accumulated to optimize the loss reduction in the regions proposed by the region proposal networks to eliminate the noise incurred. So, by estimating the feature parameters the test accuracy is improved by the optimizer. Feature engineering involves the estimation of hue, pattern texture, size, angle, and area of coverage where target samples under consideration can be a tree or a group of fruit images too. This model is implemented for disease identification on any fruit image and group of fruit images. The upscaling and resizing of feature data set leads to the accuracy of R-CNN to be increased to 98%.

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