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Optimized Feature Extraction Model on RCNN and BPNN Models for Grape Disease Detection

Prasad P. S.[1*], Dr. Blessed Prince P.[2]

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Abstract: One of the most pressing problems facing farmers today is the proliferation of plant diseases, which pose a serious threat to the safety of the food we consume. Therefore, it is crucial to detect these diseases early and find viable treatments to prevent them. This study analyses numerous methods for diagnosing and classifying diseases that might affect grapevines. The aim of this research is to provide a thorough overview of the many techniques used to identify and categorise grape leaf diseases. Important image processing procedures for disease prediction are discussed, including picture collection, data pre-processing, image segmentation, feature extraction, and image classification. Convolution Neural Network (R-CNN and BPNN are only some of the standard image processing and detection and classification methods covered. To better assist researchers in determining which methods can be selected to enhance grape leaf disease identification and classification efficiency, we have identified the differences caused by deep learing techniques and the various processes used to obtain various results by referencing a number of articles.

Index Terms: *Deep Learning, Grape Leaf , Disease, Prediction , R-CNN, BPNN*

1. Introduction

The majority of Indians work in some capacity in the agricultural sector, and this industry has traditionally been considered crucial to the country's economy. The country's enormous landmass gives farmers a wide range of potential farming locations to explore. Unfortunately, the detection of plant diseases highlights the need for the development of efficient pesticides and insecticides. Neglecting to treat a disease may have a significant effect on plant productivity and the income of the farmers who tend to such plants.

Modern technology has made it feasible to feed the world's seven billion people, and more efficient methods are always being developed to meet the rising demand for food. Still, there have been a number of factors that have threatened the food supply. Plant diseases pose another threat to food security, although early discovery of these threats may help mitigate them. The livelihood of smallholder farmers is also at risk when crop yields fluctuate, which is a major concern alongside food insecurity. It is estimated that smallholder farmers account for around 80% of the world's agricultural production, and that animals and disease account for a loss of produce of more than 50%. In addition, 50% of the hunger index is attributable to those with agricultural backgrounds, especially smallholders, because of diseases that interrupt food sources.

[1]Presidency University/Computer Science & Engineering, Bengaluru, India*
Email: prasadps@presidencyuniversity.in
[2]Presidency University/Computer Science & Engineering, Bengaluru, India
Email: blessedprince@presidencyuniversity.in
**Corresponding Author: Prasad P S*
prasadps@presidencyuniversity.in

2. Literature Review

In [1], the authors suggest a real-time system for diagnosing early stages of disease using environmental parameters such as temperature, humidity, and leaf wetness as inputs. The farmer is able to access the sensors using wireless Zig-Bee connections. The Hidden Markov Model is used to the study and forecasting of health in its earliest stages. Using a multi-class support vector machine (SVM), [2] extracts features from the RGB stream. As part of the pre-processing phase, images are optimised, shrunk, and smoothed to decrease their file sizes and processing times. K-means clustering is used to divide up images into their constituent parts. The Black rot has been measured to have an accuracy of up to 90%. [3] takes 120 pictures on location in fields using a portable camera. The accuracy of support vector machines (SVMs), backpropagation neural networks (BPNs), and fuzzy is compared and contrasted. At the outset of processing, the photo's resolution is lowered to 226x226. We have successfully converted the colour space from RGB to HSV. The absence of the backdrop allows the leaf to stand out more. Overall, it was calculated to have an accuracy of 89.3%. In order to recognise and categorise plant phenological phases from visual data, the authors of [4] employ images recorded every half an hour by the fixed cameras in combination with a convolutional neural network (CNN) model. The Alex Net classifier framework has been pre-trained. When compared to other, more conventional Machine Learning approaches, Pepper's top accuracy of 87.14% is quite remarkable. The authors of [5] collected 86,147 photos of healthy and ill plants for a public collection divided into 57 categories. The author further uses generative adversarial networks for identifying classes and separating foreground elements from the background. Resnet achieved 80% accuracy when trained on a messy dataset.

The authors of use two distinct Flower datasets in their work [6]. Combining Convolutional Neural Networks with Transfer Learning has allowed for the development of an automated technique for flower identification. Transfer learning allows us to use a pre-trained model instead of starting from scratch. Machine learning that can be trained on demand. After being converted to base 64, the user's picture is uploaded to the cloud with a single click. A convolutional neural network is then trained on the altered picture to predict the output class label based on the input labels. Overall, the Inception-v3 model performed the best, with a success rate of 98.66%.

3. Implementation

Figure 1 depicts the whole procedure for detecting grape leaf diseases with the suggested convolutional capsule networks. Collecting images, augmenting those images, splitting the dataset, building a RCNN and BPNN , classifying diseases, and analysing results are the main components of the procedure.

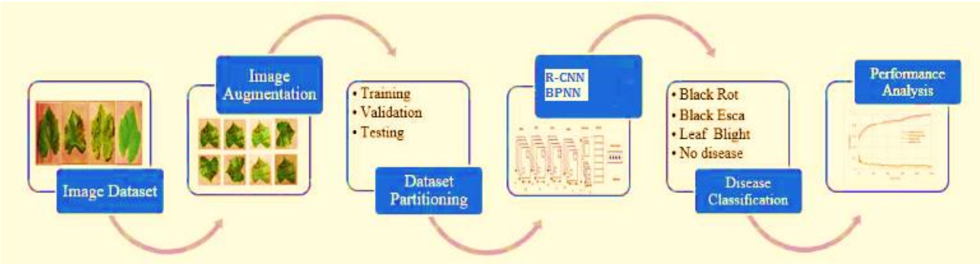

Fig 1 . Proposed Methodology

Obtaining Pictures As part of our research, we collected 2850 photos of grape leaves from the AI challenger 2018 dataset, split evenly between the training set (2,456) and the test set (3,394). Figure 1 displays several example pictures. Due to the fact that the same condition is broken down into mild and severe symptoms, the dataset has low inter-class variation. As a result, reliable illness diagnosis using a CNN model is difficult.

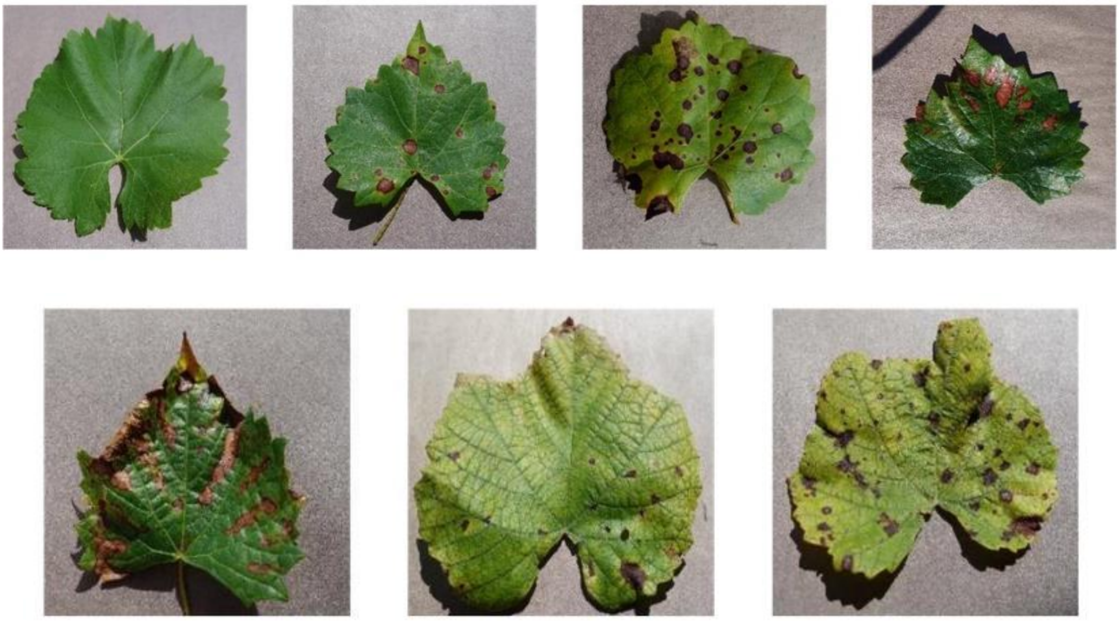

Fig 2. Examples of grape leaves. (a) GH. (b) BRF_G. (c) BRF_S. (d) BMF_G (e) BMF_S. (f) LBF_G. (g) LBF_S

Preprocessing of Images The number of grape disease samples was limited, and the distribution of samples across categories was uneven. To minimise overfitting during model training and enhance the model's generalisation capabilities, the dataset required to be extended. The procedures listed below were completed. First, we divided the training set into a training set and a validation set in a 9:1 ratio, and then we used data augmentation techniques such as rotation, colour enhancement, contrast enhancement, and Gaussian noise on the new training set. A sample of the larger pictures is shown in Figure 2. Following that, neither the validation nor test sets needed to be expanded. The validation set was used to check that the model training suited the model, and the test set was used to evaluate the model's performance. The sample distribution before and after augmentation is shown in Table 1.

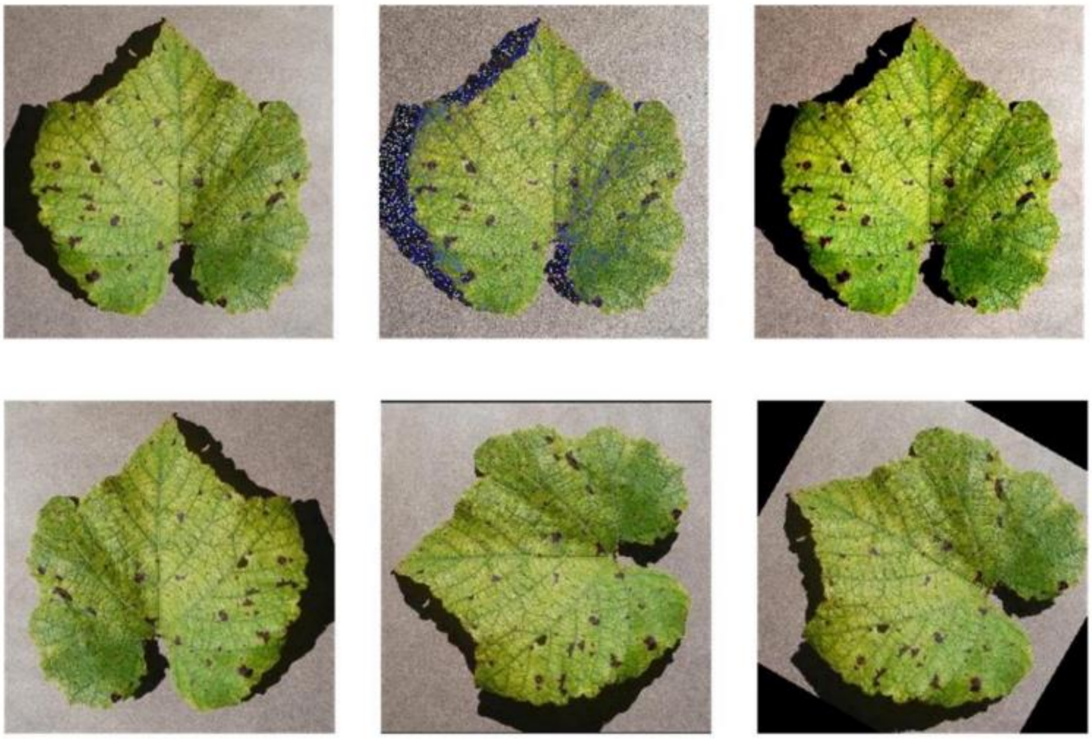

Fig 3. Expanded Images

DataSet Before Augmentation

Class	Training Data Set	Test Dataset	Validation Dataset
GH	265	42	29
BRF-G	343	54	38
BRF_S	416	66	46
BMF_G	453	74	50
BMF_S	378	59	41
LBF_G	55	9	6
LBF_S	567	90	63

Dataset After Augmentation

Class	Training Data Set	Test Dataset	Validation Dataset
GH	2650	42	29
BRF-G	2058	54	38
BRF_S	2496	66	46
BMF_G	2718	74	50
BMF_S	2268	59	41
LBF_G	1980	9	6
LBF_S	3402	90	63

3.1 BPNN Model

1) Back Propagation Algorithm

One of the most popular and useful ANN models is BPNN. It has a wide range of potential uses for nonlinear data processing. Paul and Munkvold [105] emphasised the value of BPNN in conjunction with FFNN. In an FFNN, the input layer communicates with the hidden layer, which then communicates with the output layer (forward). The BPNN's last layer of processing is the output layer. We compare the real output to a network-estimated output. Errors are computed by comparing actual output to predicted output. Error estimates are then "back-propagated," or sent from the output layer to the input layer. A wide variety of supervised learning methods exist for computing weights. The back propagation algorithm is a popular and straightforward technique for training neural networks. The primary concept here is to begin at the output layer and work backwards in order to estimate and update the weights (Gurney, 1997). The outputs of the hidden layer may be calculated using any initial random weighting matrix wih (for connecting the input nodes to the hidden layer) and whk (for connecting the hidden layer to the output nodes).

$$o_h = \frac{1}{1 + \exp - \sum_{i=1}^{n_j} w_{ih} u_i}, \quad h = 1, 2, \ldots, m$$

and the outputs for the output nodes

$$o_k = \frac{1}{1+\exp - \sum_{h=1}^{m} w_{hk} o_h}, \quad k = 1, 2, \ldots, n_o$$

3.2 RCNN Model

The author proposes a solution to the challenge of picking a large number of areas by using selective search to extract just 2000 regions (which he calls region proposals) from the picture. Consequently, rather of attempting to categorise a massive number of areas, you can now focus on only 2000 regions. Following is the selective search technique used to create these 2000 proposed regions.

Selective Search:

First, we produce the first sub-segmentation, which consists of numerous potential areas. Recursively merge contiguous sections using a greedy method Third, make your final area suggestions using the regions you just produced.

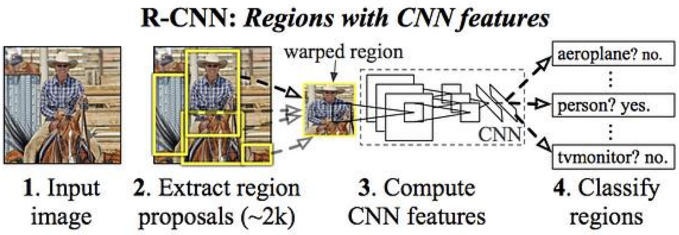

Fig 4. R-CNN with CNN Features

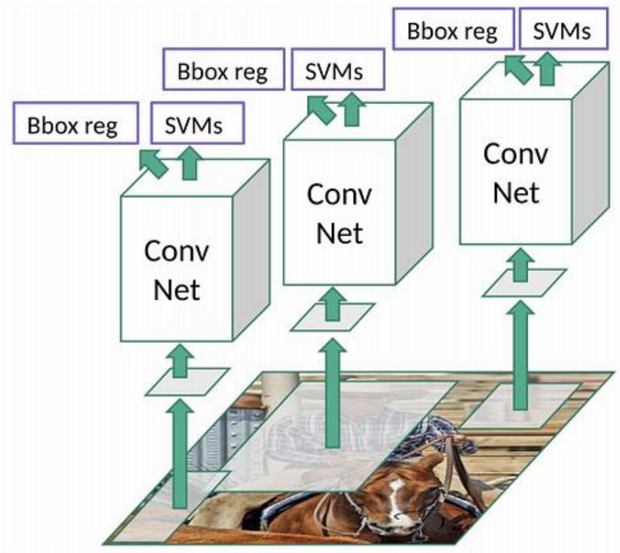

Fig 5. R-CNN Model

In order to train a convolutional neural network, we first warp the 2000 candidate area suggestions into a square and then feed that square into the network. The result is a 4096-dimensional feature vector. The CNN is used as a feature extractor, with the retrieved features making up the dense output layer; these features are then used as input to a support vector machine (SVM) for item presence classification inside the proposed candidate area. An object's existence inside the proposed regions is predicted, and the method additionally predicts four offset values to improve the accuracy of the bounding box. It's possible, for instance, that the algorithm would have correctly predicted the existence of a person inside a specific geographical suggestion, but incorrectly forecasted that their face was split in two. To modify the proposed region's bounding box, the offset values are used.

4. Results and Discussion

CNN Model	Accuracy	Recall	Precision	F1-Score
BPNN	99.2	98	94	95
RCNN	99.5	99	95	98

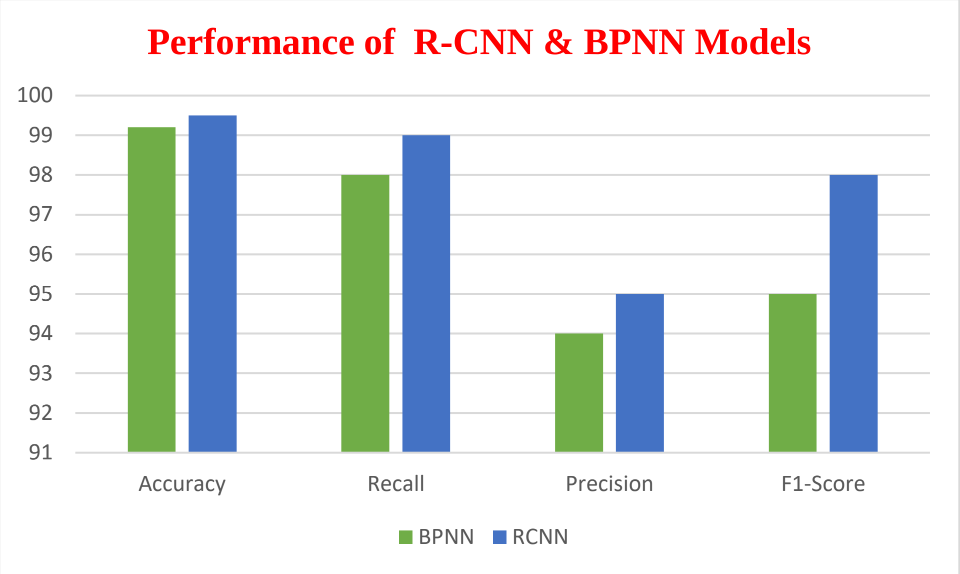

Fig 6. Performance of RCNN and BPNN

4.1 Comparison of Results

Model	Accuracy
VGG16	98.5
GoogLeNet	98
ResNet18	97.5
ResNet34	98.1
ResNet50	97.2
ResNet101	89.1
BPNN	99.2
RCNN	99.5

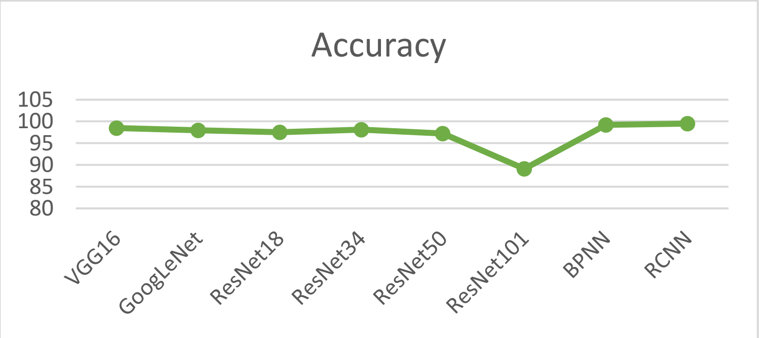

Fig 7. Comparison of CNN Models

5. Conclusion

The global agriculture industry faces a significant risk due to grape leaf disease. Therefore, modern methods of grape leaf disease detection are essential. The RCNN and BPNN models have the advantages of speed and accuracy among deep learning algorithms. Grape leaf diseases have been consistently detected using this method. It's possible that the model's recognition accuracy may suffer in relevant scenarios due to the fairly simple settings in the grape disease photographs. Our model for detecting diseases on grape leaves in the field will continue to be fine-tuned.

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