Image Based Disease Classification in Grape Leaves Using Convolutional Capsule Network

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Image based Disease Classification in Grape Leaves using Convolutional Capsule Network

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Abstract:

Crop protection is the prime hindrance for food security. The plant diseases destroy the overall quality and quantity of the agricultural products. Grape is an important fruit and major source of vitamin C nutrients. The automatic decision making system plays a paramount role in agricultural informatics. This paper aims to detect the diseases in grape leaves using convolutional capsule networks. The capsule network is a promising neural network in the field of deep learning. This network uses a group of neurons as capsules and effectively represents spatial information of features. The novelty of the proposed work relies on the addition of convolutional layers before the primary caps layer which indirectly decrease the number of capsules and speed up the dynamic routing process. The proposed method is experimented with augmented and non-augmented datasets. It effectively detects the diseases of grape leaves with the accuracy of 99.12%. The performance of the method is compared with state-of-the art deep learning methods and produces reliable results.

Keywords: disease detection, convolutional capsule network, grapes, agriculture

1. Introduction:

In agriculture, plant diseases have a vital distress because they reduce the crop quality constantly and also reduce the production. The properties of plant diseases range from minor symptoms to serious damage and thereby reduce the agricultural economy drastically [Savary, S et al., 2012]. In order to avoid the losses, different methods have been developed to detect the disease. The methods that are associated with molecular biology give correct identification of disease agents. But, these methods are not available to the farmers directly. It requires a lot of money and domain knowledge to adhere to. With the above reasons, a lot of research has been carried out to derive the methodologies which will be accurate enough and to be accessible

by the farmers. The decision making technologies are used to solve the problems of precision agriculture [Arsenovic, M et al., 2019].

In India grapes (scientific name vitis vinifera) are one of the common fruits. India is holding 18th position for the production of grapes. The Indian states of Tamil Nadu, Andhra Pradesh, Karnataka and Maharashtra are the major producing states of grapes. The grape plant grows well with the temperature of 15°C-40°C. The leaves are the paramount part of any plant. It has a long span of time in comparison with the buds and flowers. It shows the entire characteristics of plants. The leaves of the grape plants are commonly affected by black rot, black esca and leaf blight diseases. All these diseases affect the grape yield and produce loss to the cultivators [Andrushia et al., 2019, 2020]. Early detection and identification of diseases help the farmers to reduce the losses. Hence, it is essential to find the diseases by automatic systems at the earlier stages.

The latest technologies are adopted to enhance the decision making process of precision agriculture [Gebbers, R et al., 2010]. The larger amount of data has been collected from real time and various artificial intelligence techniques are used to give optimal decisions, which lead to the cost reduction. Still, the field of decision making systems in agriculture informatics is in infancy and open for improvements. It has been reviewed that various machine learning algorithms are used for this purpose. Decision trees, logistic regressions, k-nearest neighbors (KNN), support vector machine (SVM) and extreme learning machine (ELM) are the few machine learning techniques used for this purpose. The easy accessibility of cameras and the tremendous growth of internet facilities make the automatic detection system a viable one. Due to the cheap availability of gadgets, the automatic detection system is one of the less complex tasks.

The recent boom in the deep learning methods also adopted for the automatic process in agriculture. Owing to the advancement in computer memory and hardware setup can lead to extra solutions. These deep learning methods can be used to solve complex tasks in a reasonable time. This paper proposes a convolutional capsule network for disease detection and classification of grape leaves. It improves the detection accuracy and analyzes the improvements of other deep learning models. The influence of capsule dimensions on the detection accuracy is explored. By increasing convolution layers before the primary caps layers, the proposed model provides accurate detection of diseases.

The other parts of the paper is organized as follows: Section 2 elaborates the literature survey on plant disease detection. Section 3 briefly introduces the convolutional capsule network. Section 4 details about the experimental implementation and result analysis. The final section concludes the findings and limitations of the research work.

2. Motivation and related work:

Timely diagnosis of plant diseases is the prime factor to control the plant loss. If it is performed by human, then it needs lot of time, chances of getting error and costly. The automatic equipment and methods are the prime solution to monitor the crop fields [Ampatzidis et al., 2017]. Recent years, the researchers worked on the automatic techniques to detect and classify the diseases in plants. This section elaborates the computer vision methods to detect the disease in plant leaves.

Qin F et al., [2016] investigated a leaf disease detection by supervised classification algorithm. Initially, k-median and fuzzy C-means clustering methods are used to obtain lesion images. After the lesion segmentation, texture, color and shape features are extracted. The optimal features are extracted from a set of 129 features. The optimal features are trained by the machine learning methods of logistic regression, linear discriminant analysis, navie bayes and regression tree and their corresponding diseases are detected. The detection accuracy of the method depends on the adopted features and it is consuming much time.

Waghmare, H et al., (2016) investigated a system for grape plant leaf disease detection. Initially, the background of the leaf images are removed. The segmentation technique is applied to segment the diseased part of the leaves. The fractal based texture features are extracted. The extracted features are given into multiclass SVM. The proposed method classifies the grape disease of downy mildew, black rot and powdery mildew. The classification accuracy of 89% is obtained through MSVM. It varies, if the training and testing samples are increased. The size of the dataset is less and the performance metric is varied in accordance with the size of the dataset.

The need for finding automatic disease detection methods are seriously evolving due to the accomplishment of machine learning techniques. The traditional machine learning algorithms manually extract the features from the images and feed those features into a detection algorithm. It is a time consuming process and less robust. These manual feature extraction steps

make the machine learning method less versatile. But, deep learning models consist of many processing layers and fetch the features directly from the image.

Recent advancement in artificial neural network architecture made a foundation of hybrid deep learning models. Different techniques are adopted to build the deep learning based algorithm. Auto encoders, sparse coding, restricted Boltzmann machines and customized convolution neural networks (CNN) are some of the widely used architectures. Among these models CNN is mostly used for computer vision applications [Guo Y et al., 2016]. It has outstanding success in the agriculture field also. LeNet, AlexNet, ResNet, GoogleNet, Visual Geometry Group (VGG) etc., are some of the examples of CNN based models. Few studies reported the use of CNN based plant disease classification [Chen, J et al., 2019, Lu Y et al., 2017, Wang G et al., 2017, Liu et al., 2017, Ma et al., 2018, Polder, G et al., 2019, Fuentes, A et al., 2018] and yielded promising results. Table 1 highlights the plant disease classification methods for different plants.

Table 1 Deep learning based plant disease classification

References	Species	Classes	Dataset	Architecture	Accuracy
Liu B et al., (2018)	Apple	4	collected	Modified AlexNet	97.62
Amara, J., et al., (2017)	Banana	3	PlantVillage	Modified LeNet	92.88
Fuentes, A. et al., (2017)	Tomato	9	Collected	R-FCN	85.98
Liu B et al., (2020)	Grape	7	Collected	Inspection	97.22
Zilvan, V et al., (2019)	Corn	5	PlantVillage	Autoencoder	87.09
Marino, S et al., (2019)	Potato	8	Collected	CNN	-
Ma et al., (2018)	cucumber	4	PlantVillage	DCNN	93.4%
Lu et al., (2017)	rice	-	collected	DCNN	95.48%
Huang, Z et al., (2020)	Grape	5	Collected	MobileNet and improved AlexNet	97%

Ji M et al.,(2020)	Grape	7	Plant Village	Multiple CNN	98.57%

Few researchers have used CNN based models for feature extraction and the extracted features are given as inputs into machine learning algorithms for further classification. Athiwara Kun, B et al., (2015) extracted the features from CNN and fed the inputs into machine learning approaches of SVM and random forest. The performance of the model is improved in comparison with the general CNN method. Kerkech, M. et al., [2018] investigated disease detection in grapes using CNN model. The color space and vegetation indices are combined with CNN LeNet-5 to classify the diseases and obtain 95.8% of detection accuracy. This method is limited by the number of expert labeled input.

Gandhi, R et al., 2018 explored CNN for plant disease detection. The deep architectures of Inception V3 and MobileNet are used to detect the plant diseases with accuracy of 88.3% and 92%. Initial, pre-processing steps are adopted to remove the noises. Deep convolutional generative adversarial network (DCGAN) is used for augmentation steps in order to increase the number of images. The model is deployed in mobile applications. Even though the images are augmented, the detection accuracy of the model is less. Arnal Barbedo, J.G (2019) presented plant disease identification for ten different diseases. The authors increased the data samples of each disease category by gathering 60% of images under controlled conditions and 40% under real field conditions. Initially, the individual lesions and spots are segmented. After the removal of backgrounds, the pre-trained GoogleNet CNN architecture is applied to classify the diseases. The detection accuracies are varied in accordance with the plant species. The usage of spot segmentation and background removal greatly impact on the detection accuracies.

From the literature, it is understood that the deep learning models are effective to detect diseases in the plant leaves. CNNs are highly used networks which have complex layers and are used to extract the features such as rotation, translation and scale [Sezer, A et al., 2019]. The prime requirement of any CNN based architecture is massive training data which is not feasible for individual plant based image analysis. Another major shortcoming is loss of information due to local details such as position and posture during image analysis. Hence, CNNs are not a good choice for extracting diverse information such as orientation, scale and semantic class which are required for image reconstruction. Recently, Hinton team [Sabour, S et al., 2017] introduced a new deep learning architecture capsule network, which overcomes

the disadvantages of traditional deep learning techniques. It is a novel building block that represents spatial relationships of features effectively. It is mostly applied in image recognition and classification tasks. Even though the capsule network is applied to the different research fields such as tumor classification [Afshar, P et al, 2018], disease classification [Sezer, A et al., 2019, Afshar, P et al., 2020, Verma, S et al., 2020] , drug detection [Wang, Y et al., 2020], object detection [Kumar, A.D, 2019], hyper spectral image classification [Deng, F et al., 2018, Yin, J et al., 2019, M. E. Paoletti et al., 2019], it is still in infancy. Actually, a capsule network uses a set of neurons as a capsule. The capsules are vectors to denote internal properties that can be utilized to learn the relationship between various features. So, the potential variant can be effectively inferred by the model with lesser training inputs.

Few studies only used the capsule network in plant disease analysis, because it is one of the recent techniques in the field of computer vision. The limitations in the field of plant diseases detection are listed below: reduction in trainable parameters to design an efficient network, development of an efficient model to detect the plant diseases for a large dataset. These limitations are addressed in the proposed method. The novelty of the work is as follows: the proposed method combines CNN and the capsule network to obtain superior results in comparison with the state-of-the-art methods. The convolutional layers are added before the primary caps layer which indirectly decrease the number of capsules and speed up the dynamic routing process.

The influence factors of the proposed model are dimension of capsules and routing number of training phases which are analyzed towards classification results. It can give valuable guidance for subsequent research on plant disease classification using a capsule network.

3. Materials and Methods

The complete process of proposed grape leaf disease detection using convolutional capsule networks is highlighted in figure 1. The key steps which are involved in the process are image collection, image augmentation, dataset partitioning, convolutional capsule network, diseased classification and performance analysis.

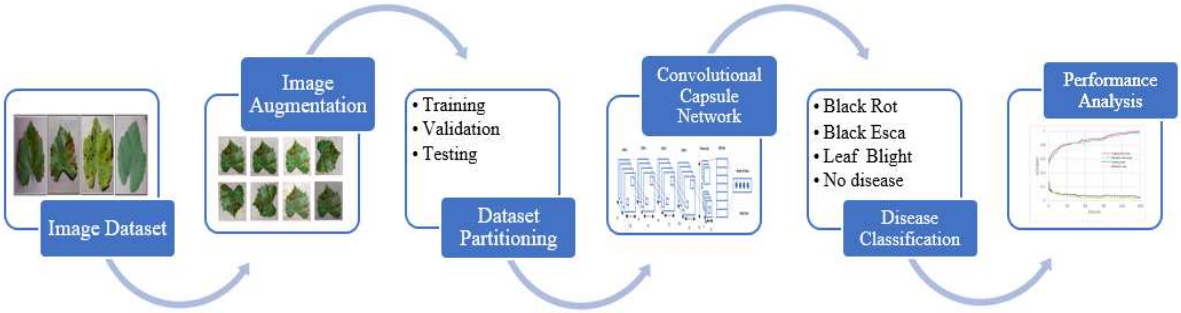

Figure 1: Flow chart of proposed grape leaf disease detection

3.1 Dataset

In this study, the grape leaves dataset is collected from the farms which are cultivating grape plants. The images are captured in the grape fields that are located in Madampatti, Coimbatore district, Tamil Nadu, India. In addition with this, the images from plant village dataset [Hughes DP et al., 2015] also used for the proposed experiment. The healthy grape leaf images and diseased leaf images are taken. The considered disease categories are grape black rot, grape esca and grape leaf blight. Figure 2 shows the images under each disease category.

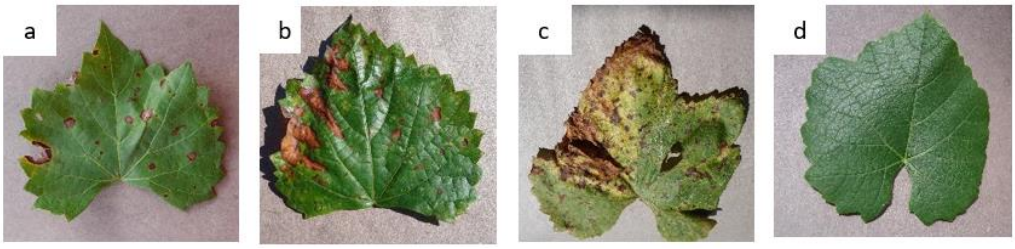

Figure 2: Images of grape leaf diseases classes (a) black rot (b) black esca (c) leaf blight (d) No disease

3.2 Capsule Networks

Capsule network has a deep learning architecture. It handles affine transformation well [Deng, F et al., 2018]. The capsules of the capsule network are designed to represent the output in terms of vectors. The capsules consist of a set of neurons that can learn the entities of an image such as pose, size and orientation. Dynamic routing mechanism is followed to route the data from one layer to another layer. The lower layer capsules predict the response of higher level capsules. The higher level capsules are triggered only when the lower level predictions agree. Consider 'i' is the lower level capsule and its output is μ_i. The prediction of higher level capsule 'j' is given by

$$\tilde{\mu}_{j|i} = W_{ij}\mu_i \qquad (1)$$

Where W_{ij} is the weight matrix. It is learnt by back propagation technique. Each and every capsule try to predict the response of the higher level capsules. If the prediction of the capsule imitates the actual response of higher level capsules, then the coupling coefficients between the capsules will increase. The coupling coefficient can be calculated by following equation:

$$C_{ij} = \frac{e^{b_{ij}}}{\sum_k e^{b_{ij}}} \qquad (2)$$

Where b_{ij} is the log prior probability. It is given as zero initially which highlights whether lower level capsule 'i' is coupled with higher level capsule 'j'. By using equation 3 the input vector of higher level capsule j is calculated.

$$S_j = \sum_i C_{ij}\ \tilde{\mu}_{j|i} \qquad (3)$$

The length of the output vector shows the probability of existence. The nonlinear squash function is used as ant activation function. It shrinks long vectors close to one and chokes short vectors to almost zero. It is given by,

$$V_j = Squash\ (S_j) = \frac{\|S_j\|^2}{1 + \|S_j\|^2}\frac{S_j}{\|S_j\|} \qquad (4)$$

The input and output vector of jth capsule is represented by S_j and V_j. The equation 1 to 4 is used for the routing procedure to find V_j. The routing number can decide the number of iterations. The output length of lower capsules encodes the existence probability of their entities [Zhang, W et al., 2019]. The vector directions encode different properties of the entities such as orientation, size and posture. So, the capsules learn the spatial relationship between entities within the input image. The margin loss is used to detect if the entities of the particular class are present and can be obtained by equation 5. 'k' is the last layer of the capsule and l_k is the loss function.

$$l_k = T_k \max(0, m^+ - \|V_k\|)^2 + \beta(1 - T_k)\max(0, \|V_k\| - m^-)^2 \qquad (5)$$

If T_k is one then 'k' is present. At the initial training process, the parameters of m^+, m^- and β are indicated. The sum of the losses of all output capsules of the output layer is known as total loss.

3.3 Convolutional Capsule Network

The proposed method uses convolutional capsule networks for the disease classification of grape leaves. The architecture of the convolutional capsule network of the proposed method is shown in figure 3. The input image of size 128 × 28 is used for the classification. The architecture consists of 5 convolution layers, 1 primary layer, 1 digit layer and 3 fully connected layers. In order to generate an effective feature map, more convolutional layers are added. Initial layer consists of a 5×5 size of 16 convolutional kernels with 1 stride. 2×2 max-pooling with 2 strides is performed after the first layer. The second layer consists of a 5×5 size of 32 convolutional kernels with 1 stride. The third layer consists of a 5×5 size of 64 convolutional kernels with 1 stride. 2×2 max-pooling with 2 strides is performed after the second and third layer. The fourth layer consists of a 9×9 size of 128 convolutional kernels with 1 stride. Primary capsule layer is the fifth layer which consists of 32 capsules. Each capsule is applied with a 9×9 size of convolutional kernel with stride 1. The digit caps layer consists of 16 dimensional capsules with four classes.

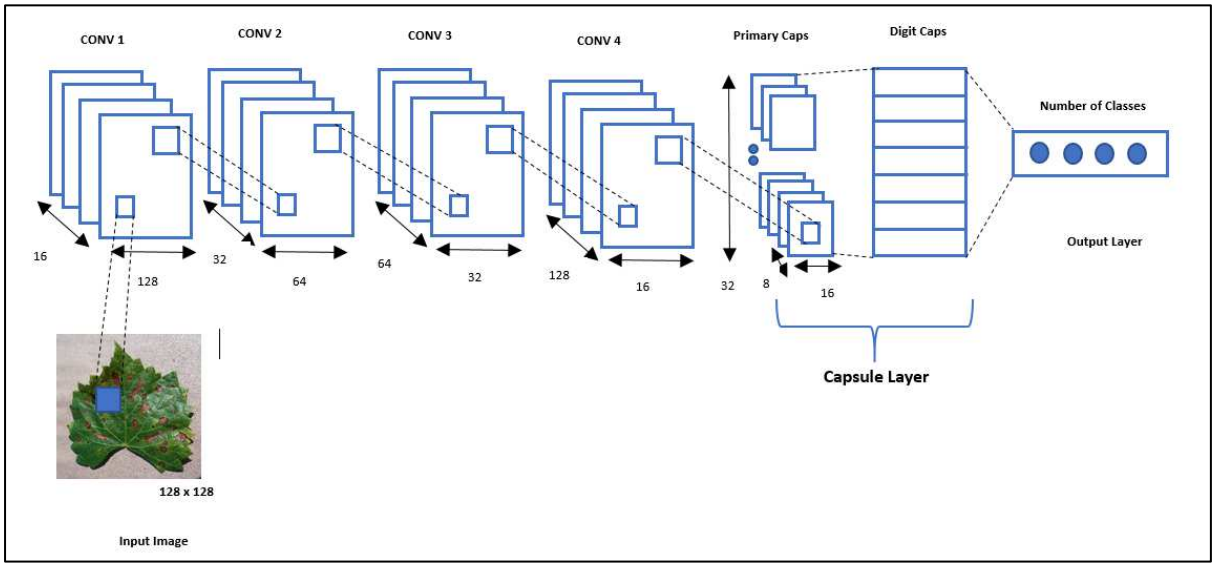

Figure 3: The convolutional capsule network for grape disease classification

3.3.1 Pre-processing and data augmentation

The input size of the proposed model is 128 × 128. The size of the images in the input dataset are not the same. So, all the images are resized into 128 × 128. Inadequate inputs cause overfitting problems in the deep neural network. In order to avoid overfitting problems, the

input images are augmented. Rotation, scaling transformation, gamma correction, flipping and color augmentation techniques are used to generate the augmented dataset. The augmented images are randomly shuffled and grouped into training, testing and validation dataset. Figure 4 shows the example of augmented images. Table 2 highlights the number of grape leaf images under each category.

Table 2: Details of image augmentation

Types	Number of images	
	Without data augmentation	With data augmentation
Grape black rot	2800	7000
Grape black esca	2500	7000
Grape leaf blight	2000	6000
No disease	4000	8000
Total	11300	28000

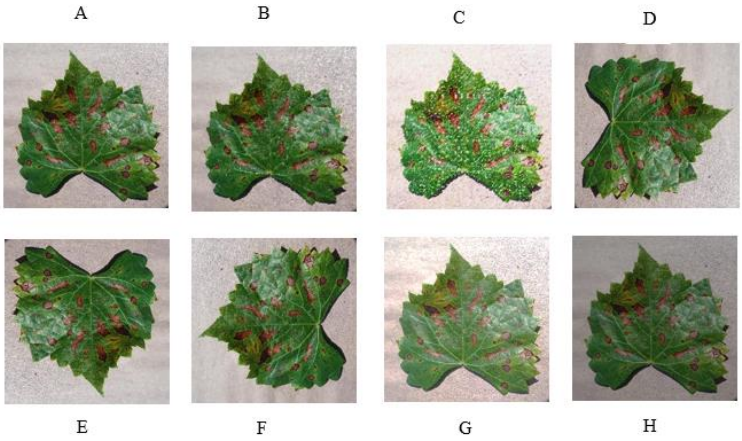

Figure 4: Data augmentation results (A) input image (B)-(H) augmented images

3.3.2 Optimization of hyper-parameter

The hyper-parameter optimization of convolutional capsule networks depends on the number of kernels in the convolutional layer, dimensions of primary caps and digit caps layers. In addition, routing number is one of the vital parameters to find coupling coefficients. It is tested from 1 to 3 with an increment of 1. The performance of the architecture is tested for each parameter setting. Based on the training dataset ten-fold cross validation is adopted. After achieving highest accuracy, the best set of parameters are chosen and applied for testing the dataset. In order to reduce overfitting, early stopping is adopted. Whenever the error in the

validation set is less than the previous iteration, the training is stopped immediately and the optimal hyper-parameter is derived.

Table 3: Hyper-parameter of convolutional capsule network

Hyper-parameter	setting
Activation	ReLU
Maximum Epoch	150
Optimizer	Adam
Batch size	50
Routing Number	1-3
Learning rate	0.0001
Number of kernels in Conv1 layer	16
Number of kernels in Conv2 layer	32
Number of kernels in Conv3 layer	64
Number of kernels in Conv4 layer	128
Number of kernels in Primary Caps layer	256

3.3.3 Training of Convolutional Capsule Network

During the training process, the weights of convolutional neural networks are randomly initialized using normal distribution with 0.01 standard deviation. Rectified linear unit activation function is used in all layers of the network. Batch normalization is used to reduce the internal covariate shift. The input of each layer is normalized to the standard Gaussian distribution [Ioffe, S et al., 2015]. The Adam optimizer of stochastic gradient descent algorithm is utilized as the optimizer. This algorithm learns sparse data and fine tunes the learning rate for every parameter setting. In comparison with non-adaptive methods, it has a high convergence rate.

Let *c1,c2,c3,c4,p5* are the parameters of four convolutional layers and the primary caps layer. The convolutional operations are represented with *conv*. The output from the convolutional layers and primary caps are denoted by *O_conv1, O_conv2, O_conv3, O_conv4 and O_prim*. Feature extraction process is achieved through convolutional layers and primary caps layer. The dynamic routing is used to generate digit capsules. The stochastic gradient is used to find the network parameters. The detail algorithm for training convolutional capsule network is given below:

Algorithm

Input:

Feature vector (F)
No of training epoch (E)
No of dynamic routing iteration (R)

Output:

Capsule length (L)

for n=1 to E do

O_conv1 ← conv (F,c1); O_conv2 ← conv (c1,c2); O_conv3 ← conv (c2,c3);
O_conv4 ← conv (c3,c4); O_prim ← conv (c1,p5);
μ←encapule(O_prim)
for capsule 'i' in primary caps layer
compute $\tilde{\mu}_{j|i} \leftarrow W_{ij}\mu_i$ (Equation 1)

for capsule 'i' in primary caps layer and capsule 'j' in digit caps layer

$b_{ij} \leftarrow 0$

for m=1 to R do

for capsule 'i' in primary caps layer
$c_i \leftarrow \text{softmax}(b_i)$ (Equation 2)
for capsule 'j' in digit caps layer
compute $S_j \leftarrow \sum_i C_{ij}\ \tilde{\mu}_{j|i}$ (Equation 3)
for capsule 'j' in digit caps layer
$V_j \leftarrow Squash\ (S_j)$ (Equation 4)
for capsule 'i' in primary caps layer and capsule 'j' in digit caps layer

$b_{ij} \leftarrow b_{ij} + \tilde{\mu}_{j|i}.V_j$

End for

L← length of V
Compute loss (Equation 5)
c1←c1-$(\partial L/\partial c1)$

c2←c2-$(\partial L/\partial c2)$

c3←c3-$(\partial L/\partial c3)$

c4←c4-$(\partial L/\partial c4)$

p5←p5-$(\partial L/\partial p5)$

End for

3.4 Performance Assessment

K fold is the efficient cross-validation method which is used for larger dataset. 10-fold cross validation is used to evaluate the performance of the proposed method. The dataset is randomly separated into ten subset. Of the 10 subsets, 9 subset is used for training and the remaining dataset is used for testing the network. The cross validation procedure is repeated 10 times.

With each of the ten subsets used exactly once as the validation set. The performance of the method is obtained by taking an average of all ten runs.

The performance of the proposed method is assessed through precision, recall, f-measure and accuracy. Precision is used to quantify the number of positive observations to the total observation. Recall is used to quantify the number of positive observations made out of all positive samples. F1 measure or F1 score is the weighted average of precision and recall which replicate the total number of observations that are correctly classified by the network. The equations of the performance metrics are given below,

$$Precision\ (P) = \frac{TP}{TP + FP} \qquad (6)$$

$$Recall\ (R) = \frac{TP}{TP + FN} \qquad (7)$$

$$F1\ Measure\ (F1) = \frac{2TP}{2TP + FP + FN} \qquad (8)$$

$$Accuracy\ (A) = \frac{FP + FN}{TP + TN + FP + FN} \qquad (9)$$

4. Experimental results and discussion

The proposed method for convolutional capsule network based grape leaves disease detection and classification is implemented in the system having 2.90 GHZ processor with 12 GB RAM and 4 GB GPU card NVIDIA GTX 1050. All the calculations are carried out in the aforesaid system. Epochs are varied in the range of 30-150 with respect to the testing accuracy. The learning rate is varied from 0.01to 0.0001 Different batch sizes are tried for the network in order to fit in the GPU. The batch size varies from 5 to 50. In order to cater the computer memory, it is fixed as 50. Different volumes of training parameters are considered with respect to the dataset in the training process. 85% of the dataset is used for training and 15% of dataset is used for testing. The optimal set of hyper-parameters are listed in table 3. The detailed quantitative and qualitative analysis is carried out for augmented and non-augmented datasets.

4.1Performance Analysis

All the images in the dataset are resized into 128 × 128. The collection of image dataset for diseased grape leaves is a time consuming process. The image augmentation steps are used to provide sufficient images for training and testing of the model. The proposed convolutional capsule network for grape disease detection and classification is experimented for two datasets (with and without augmentation). It is trained with optimal hyper-parameters. The performance

of the model is evaluated for 10 fold cross validation. In the training process, epochs play vital role in order to check the performance of the model. The proposed method has been tried with different epochs which are starting from 30. The model has converged after 150 epochs. Hence, the training accuracy and loss of the model is obtained up-to 150 epochs.

Table 4: 10-fold cross validation results of augmented dataset

Folds	P %	R %	F1 %	A %
Fold 1	99.23	97.21	97.43	97.23
Fold 2	97.12	99.17	98.25	98.21
Fold 3	98.37	99.20	99.27	99.25
Fold 4	98.44	99.92	99.72	99.81
Fold 5	98.53	99.98	99.81	99.66
Fold 6	98.45	99.23	99.92	99.86
Fold 7	99.11	99.23	98.63	98.65
Fold 8	98.23	99.21	99.16	99.12
Fold 9	98.45	98.36	99.42	99.34
Fold 10	98.13	99.13	99.83	99.76
Mean	98.41	99.06	99.10	99.12

The performance metrics of the proposed method for augmented dataset and non-augmented dataset are highlighted in table 4 and 5. The detailed results of 10-fold cross validation is shown. The experimental results highlight that the classification accuracy is high for augmented dataset. 99.12% of classification accuracy is obtained by convolutional capsule network for augmented dataset. Recall is one of the important performance metrics which is used to minimize the false negatives. In the proposed method, the recall value is as high as 99.06%. Adding convolutional layers in the capsule network and the parameters which are employed in the network results in accurate detection of grape leaf diseases.

Table 5: 10-fold cross validation results of non-augmented dataset

Folds	P %	R %	F1 %	A %
Fold 1	98.13	94.10	94.92	95.11
Fold 2	93.12	85.31	89.04	90.10
Fold 3	83.84	83.23	83.67	88.45

Fold 4	91.32	90.10	89.75	89.94
Fold 5	95.13	87.71	91.01	91.12
Fold 6	98.11	93.13	95.52	95.72
Fold 7	82.98	87.92	84.23	85.61
Fold 8	97.01	92.33	94.51	94.61
Fold 9	83.46	83.22	83.13	88.61
Fold 10	87.89	86.96	85.96	90.32
Mean	91.01	88.51	89.23	92.13

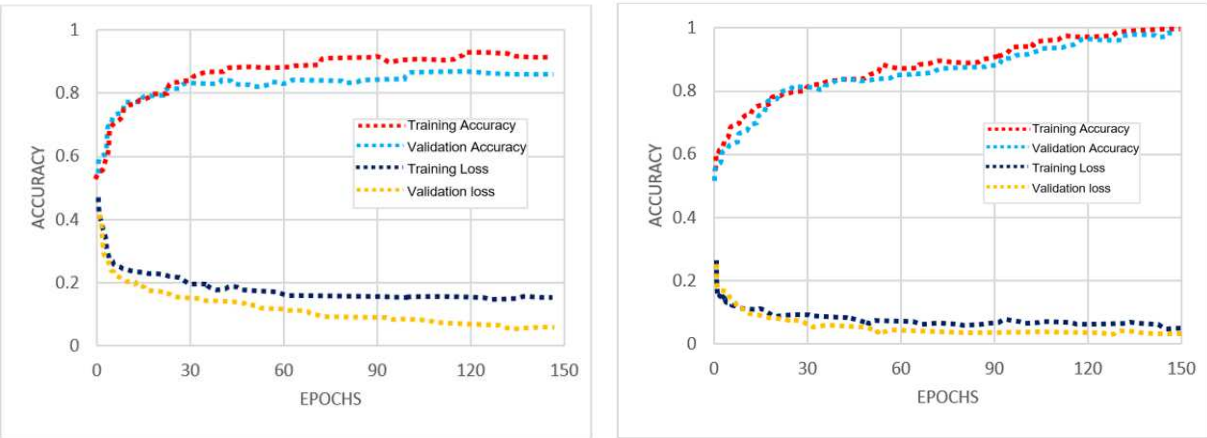

Figure 5: Training and loss graphs of non-augmented dataset (left) and augmented dataset (right)

Figure 5 shows the graphs of performance metrics under training and validation phases. The epochs play a paramount role in the learning process of deep learning models. The proposed model of convolutional capsule network for grape leaves disease classification achieved 99.12% of validation accuracy and 0.091loss. It is for augmented dataset. For non-augmented dataset the validation accuracy is 92.13% and loss is 0.132. Around the 120th epoch the high accuracy is obtained but it is not consistent. It converged after 150 epochs. The proposed model is trained for augmented dataset and non-augmented dataset in which the augmented datasets give higher performances.

4.2 Experimental Parameters Analysis

4.2.1 Capsule Dimensions

The capsules are an important component of the convolutional capsule network. It consists of many neurons. The capsules in the primary caps layer are the lower level capsules. It learns from convolutions layers and it can represent small entities of the input image. The capsules in the digit caps layers are higher dimensions which represent the complex entities of the input. Hence, the dimensions of the capsule play a major role in the classification tasks. If the dimensions of the capsule are low then the representation ability of the capsule is less. In addition, if the dimensions of the capsule is high then the redundant information will occur. Both cases provide negative results in the classification. The set of values for capsule dimensions [(4,8), (6,12), (8,16), (10,20)] are used to evaluate the performance of the model. The other parameters are given as per table 3. The effect of capsule dimensions over two datasets are given in figure 6. D1 is an augmented dataset. D2 is a non-augmented dataset. The classification accuracy is high for the capsule dimensions of (8,16). The performance of the model gradually increases, as the dimension increases. When the dimensionality is too high then it causes dimensional disaster and results in performance degradation.

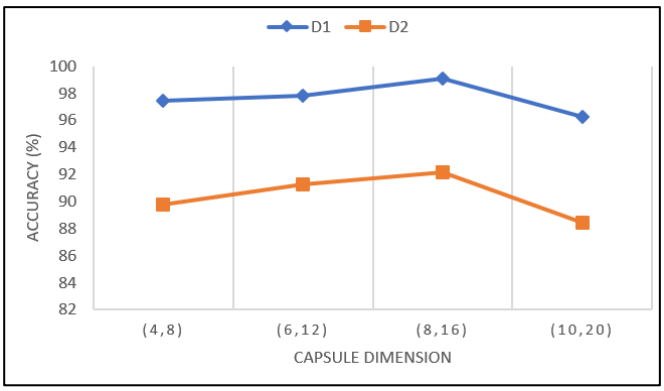

Figure 6: Effect of capsule dimensions

4.2.1 Routing Number

The routing number is the prime factor to detect whether a capsule network can obtain accurate coupling coefficients. Hence, it is necessary to determine the optimal routing number. In this experiment, the routing number is checked for 1,2 and 3. The network used other parameters which are listed in table 3. Figure 7 shows the effect of routing number with respect to the accuracy. By increasing the routing number the accuracy is increased initially. Afterwards it

decreased. If the routing number is high, then the training time of the network is also high. Hence, the optimal routing number 2 is chosen in this experiment.

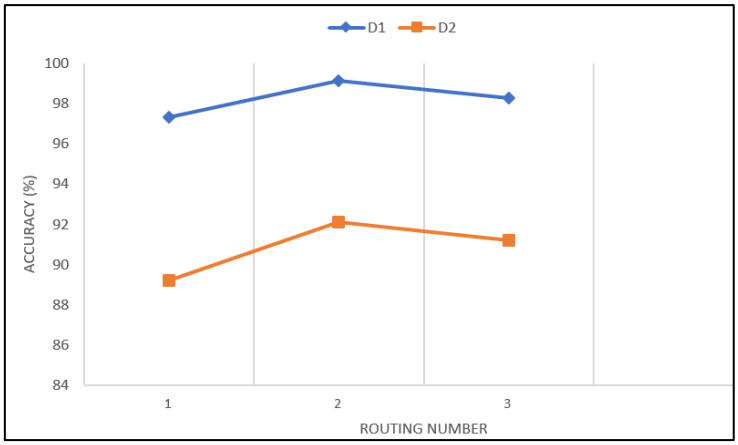

Figure 7: Effect of routing number

4.3 Time complexity

In the proposed work, a convolutional capsule network is used to detect the grape leaves diseases. The network consists of convolutional layers before the primary caps layer. It decreases the number of primary capsules and speeds up the dynamic routing process. As the network uses dynamic routing over multiple iterations, the number of operations is higher, but it also makes the entire network converge quickly. Hence, the design complexity of the network also reduced. The time complexity is based on the required number of multiplications in the capsule layer and fully connected layers. The lower layer capsule 'i' having the dimensions of d_1 and the higher layer capsule 'j' having dimensions of d_2. By considering 'k' capsules in lower layers and 'm' capsules in the higher layer, the total number of operations is $m \times d_2 \times k \times d_1$. Each prediction involves $d_1 \times d_2$ multiplications. According to equation 3 each capsule is calculated as a weighted average over predictions. d_2 multiplications involved to weight each prediction $(\tilde{\mu}_{j|i})$with coupling coefficients (C_{ij}). Each routing process includes $d_2 \times k \times m$ multiplications. The capsule networks have less number of layers in comparison with convolutional neural networks. The proposed method took 1.82 seconds to process each input in the NVIDIA GTX 1050 computer.

4.4 Comparative Analysis

The performance of the proposed method is compared with five state-of-the-art deep learning methods. All the methods have adopted a deep learning network for grape leaves disease detection. Recent research works which are undergone for grape leaves disease detection

methods only selected for the comparison. Table 6 shows the comparative deep learning methods.

CNN based architectures are used mostly to detect the diseases in grape leaves. Most Kerkech, M. et al., [2018] investigated disease detection using CNN model. The color space and vegetation indices are combined with CNN LeNet-5 to classify the diseases and obtained 95.8% of detection accuracy. The real time datasets are used in this method. Xie, X et al., [2020] experimented the disease detection of grape leaves by faster R-CNN model. The pre-trained models of Inception v1, Inception ResNet v2 blocks are used to derive faster DR-IACNN model. The implementation results highlight that faster IACNN method produces 81.1% of average precision. The four common diseases of grape leaves are classified. The real time grape leaf disease detection dataset (GLDD) is used. The improved convolution neural network (DICNN) is used by Liu B et al., [2020] to detect the common diseases of grape leaves. 97.22 % of detection accuracy is obtained by DICNN model. It is higher than the GoogleNet and ResNet-34 model. Rao U.S et al (2021) explored disease detection for mango leaves and grape leaves. The pre-trained model with AlexNet is used to detect the diseases. The plant village datasets and real time datasets are used. 99.03% of detection accuracy is obtained. Huang et al (2020) explored transfer learning based disease detection for grape leaves. The real time self-acquired dataset is used for the study. The pre-trained models of VGG16, MobileNet and AlexNet was used. MobileNet and improved AlexNet produced 97% of classification accuracy. Ji M et al (2020) used multiple CNN to extract the complementary features from the input. Inception V3 and ResNet50 based CNN architecture is used to detect the diseases. 98.57% testing accuracy is obtained by the model. The grapevine yellow disease is analysed through various CNN models [Cruz, A et al., 2019] in which ResNet-50 produced better performance.

Table 6: Comparative analysis with state-of-the-art methods

References	**Algorithm**	**Selected plant**	**Datasets**	**Performance metric**
Liu B et al., [2020]	DICNN	Grape	Real time images	Accuracy 97.22%
Kerkech, M. et al., [2018]	CNN-LetNet	Grape	Real time images	Accuracy 95.8%
Xie, X et al., [2020]	DR-IACNN	Grape	Real time images	Precision: 81.1%
Rao U.S et al (2021)	Transfer Learning with AlexNet	Grape	Plant village+real time dataset	Accuracy 99.03%

Huang, Z et al., (2020)	MobileNet and improved AlexNet	Grape	real time dataset	Accuracy 97%
Ji M et al.,(2020)	Multiple CNN	Grape	Plant Village	98.57%
Proposed	Convolutional Capsule Network	Grape	Plant village+real time dataset	Accuracy 99.12%

4.5 Discussions

The automated systems with deep learning techniques produce reliable results in most of the pattern recognition problems. Among these deep learning techniques, CNN is largely used by the researchers for image classification tasks. Even though CNN is used extensively, there are few disadvantages. It fails to set relationships among spatial relationships such as posture, size, orientation etc. The prime reason is that the input is processed through subsampling and max pooling techniques.

The first capsule networks were proposed by Hinton (Sabour et al., 2017). This network received attention from the researchers because of its performance. The remarkable performance of the network is based on the dynamic routing algorithm. The capsule is a set of neurons that are in the form of a vector. These vectors represent the input information in terms of spatial orientation, magnitude etc., The capsules are routed via dynamic routing from one layer to another layer. It will catch and hold many fine information than conventional deep learning models. Nevertheless, the small changes in the input vector components are often neglected by deep learning techniques. The capsule networks adopt vector neurons to have a better performance than the other deep neural models.

The proposed method combines CNN and the capsule network to obtain superior results in comparison with the state-of-the-art methods. The novelty of the proposed work depends on the additional convolutional layers which are added before the primary caps layer. These layers indirectly decrease the number of capsules and speed up the dynamic routing process. The influence factors of the proposed model are dimension of capsules and routing number of training phases which are analyzed towards classification results. It can give valuable guidance for subsequent research on plant disease classification using a capsule network.

The major advantages of proposed method are listed below:

In this work, the convolutional capsule network is used to detect the diseases of grape leaves. Unlike CNN, the diseases from grape leaves are detected from a small number of layers. Four convolutional layers and primary capsule layers are used. The CNN model several convolutional layers are used to detect the diseases of the same task [Geetharamani, G et al., 2019, Ghoury, S et al., 2019]. Less number of layers make the network to be less complex. In order to increase the reliability of the automatic system, a large number of images are used for comparison with previous studies. By decreasing the size of the input image, the information in the image is lost. In the proposed method, even though the input image is given with the size of 128 x 128, reliable classification is achieved. The CNN based models used the input images with size higher than 128 x 128 [Xie et al.,2020].

The major limitations of the research work are listed below: When processing large images, the convolutional capsule network requires a lot of hardware resources. There is no standard rule for finding the number of primary caps. It is discovered artificially by the convolution mode of the convolution layer.

5. Conclusions:

The automatic plant disease detection system is a universal detector which detects the abnormalities caused by fungal and bacterial deformities. In this work, a convolutional capsule network is used to detect the diseases on grape leaves. CNN is immensely used in several agricultural applications. The major shortcomings of CNNs are addressed by the capsule network. In the proposed convolutional capsule network, convolutional layers are added before the primary caps layer which indirectly decrease the number of capsules and speed up the dynamic routing process. The influence factors of the proposed model are dimension of capsules and routing number of training phases which are analyzed towards classification results. The experimental results are evaluated under augmented and non-augmented datasets. The proposed model yields 99.12% of classification accuracy. The performance of the proposed method is analyzed through the performance metrics of precision, recall, f1 score and accuracy.

In future, the research work can be extended by adding additional disease classes of grape leaves. The above work can be extended by developing an automatic drone which can compute the overall health of fields and take immediate actions. It will empower the farmers and much useful to decrease the losses of fields.

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Compliance with ethical standards

Conflict of interest

Authors declare that they have not conflict of interest.

Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors.

Data Availability

The datasets generated and analysed during the current study are available from the corresponding author on reasonable request.

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