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Betel Vine disease detection and classification using ResNet-101

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ABSTRACT

Betel vine leaves diseases caused by regular endangerment to bacteria which causes a huge yield loss globally. In recent years, deep learning has shown great potential in the field of image classification. Machine learning, the latest breakthrough in computer vision, is encouraging for fine-grained disease classification, as the method uses SVM classifier and Gaussian mixture model for image segmentation. Disease detection and classifications are considered as the two hardest works to the recognition of Betel vine disease. Betel vine is an important crop in many tropical countries and its classification is important for various applications such as variety recognition and quality control. However, due to its complex and diverse structures, betel vine classification remains a challenging task. One popular deep learning architecture is ResNet, which has been widely used for image classification tasks and has achieved good performance on various benchmark datasets. Thus, this work uses ResNet architecture to identify and classify the betel vine disease. Dataset of betel vine images and preprocessed the data to prepare it for use with the ResNet101 architecture. ResNet101 architecture is a promising method for betel vine classification. The model performs well in terms of precision and recall demonstrating its effectiveness for betel vine classification.

Keywords: ResNet, SVM, Convolutional Neural Network, Gaussian Mixture Model, Histogram Equalization

1. INTRODUCTION

India is known as the best producer of betal vine leaf which is mostly present in forest area about 59,76 acres land. It is a very profitable cultivation and it used to cure many pathenogenic diseases because it contain huge medical content in the betal vine leaf. Betal vine plant is traditional, economically and medically important all over the world. It can also helps to treat communicable and non-communicable diseases like cough, cold, asthma, stomachalgin but also treat other diseases conjunctivitis, constipation, swelling of gums, cuts and injuries.

Due to many bacterial, fungal diseases the betal leaf lost its benefits. Because of poor quality leaf, farmer did not get the good market price. There are lot of factor that can affect the normal performance of betal vine leaf. In conclusion, the production of the betal vine is demonstrated. This infections of Betal vines can be put to end with appropriate treatment and steps. In order to minimized the infections robotic system is developed and the behaviour of the betal leaf can be analysed.

However, the excessive and widespread use of these chemicals can harm human health as well as the environment, for this reason the identification and classification of plant leaf diseases still an important role in agriculture. Therefore, an automatic system needs to be developed to control this disease very early, identification of betel vine leaf diseases using some automatic techniques is very useful as it decrease the work of supervision especially in big fields of production, one such technique is the automatic classification of betel leaf diseases using deep learning models, automatic classification of betel leaf diseases is an important research topic performed to provide benefits to the farmer as it is important in controlling large fields of crops and at a very early stage and very rapidly. The work will help then to solve farmers problems of plant’s disease identification, it will thus help them cure the plant’s disease in early stage and will thus increase the quality and the quantity of crops, and therefore help in increasing farmer’s profit.

2. LITERATURE SURVEY

In the existing work,[2] -[4], the problem of image classification has been addressed as a two-stage approach: the extraction of handcrafted features and machine-learning classification. The feature extraction step is regarded as the most important stage because the subsequent classification task is based Convolutional Neural Networks for Texture Feature Extraction on the derived image descriptors. Even the most powerful machine-learning classifier will provide a poor classification performance if the image features are not chosen appropriately. The extraction of relevant and discriminative features is a challenging task for real-world applications. Moreover, images are captured under various conditions and, to obtain good classification results, the extracted features should provide invariance to several transformations (such as scale, rotation, illumination conditions) and robustness to noise.The accuracy level is 80%-85%.

Raul Malutan et al. [5], proposed CNNs method proves to be more efficient in terms of processing times and discrimination and analysed the classification results obtained by extracting features. analysed the classification results obtained by extracting features from several different layers of the different CNN pre-trained models and using them for describing the textures in the datasets. CNNs Method obtained accuracy level of 83%.

Argüeso et al. [6] taken 38 kinds of plant disease images in the public dataset P1antVillage as the identification object, Siamese networks, and triplet loss was used and compared to classical fine-tuning transfer learning. The median accuracy was 55.5 % learning for 1 image per class. Median accuracy were 80.0 % and 90.0 % for 15 and 80 images per class. The FSL method outperformed the classical fine-tuning transfer learning which had an accuracy of 18.0 % and 72.0 % for 1 and 80 images per class, respectively

Wang and Wang et al. [7] proposed a fewshot learning method based on the Siamese network with contrastive loss and kNN classifiers to solve plant leaf classification problem with a small sample. The accuracy level is 72%. Das and Lee et al. [8] proposed a two-stage multilayer neural network for the few-shot recognition of new categories and a detailed mathematical theory derivation process.The performance metric is k-shot accuracy of 80.3%.

Chai et al. [13] studied four tomato leaf diseases, including early blight and late blight leaf mildew and leaf spot, and extracted 18 characteristic parameters such as color, texture, and shape information of tomato leaf spot images, using stepwise discriminant and Bayesian discriminant principal component analysis (PCA), respectively. Principal component analysis and fisher discriminant methods were used to extract the characteristic parameters and construct the discriminant model. The accuracy of the two methods reached 94.71% and 98.32%, respectively.

Li and He [14] selected 5 kinds of apple leaf diseases (speckled deciduous disease, yellow leaf disease, round spot disease, mosaic disease, and rust disease) as the research objects. By extracting 8 features of the apple leaf spot image, such as color, texture, and shape. The BP neural network model was used to classify and recognize the diseases, and the average recognition accuracy reached 92.6%.

Guan et al. [15] extracted 63 parameters including morphology, color, and texture features of rice leaf disease spots, and applied step-based discriminant analysis and Bayesian discriminant method to classify and recognize three rice diseases (blast, stripe blight, and bacterial leaf blight) with the highest recognition accuracy of 97.2%

The rest of the article is followed in this section illustrated the existing work in various techniques and provide their accuracy.

3. EXISTING WORK

A. BLOCK DIAGRAM OF EXISTING WORK

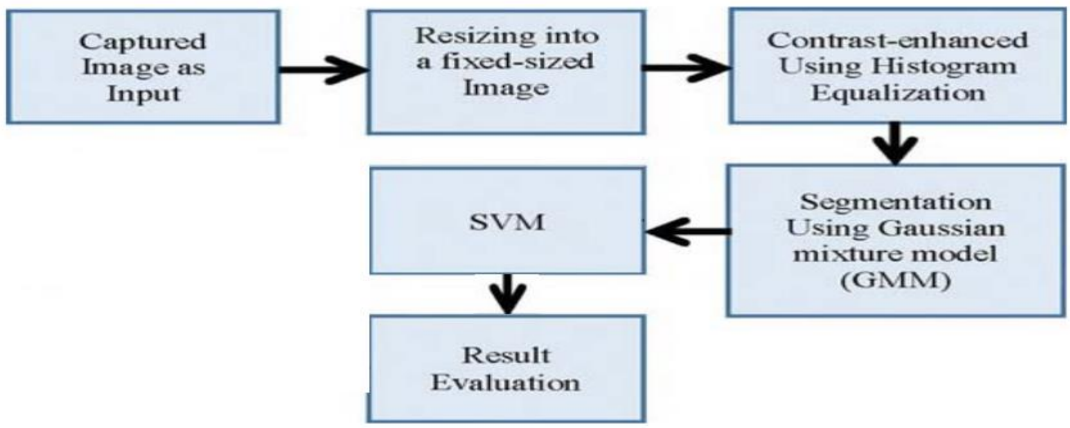


Fig. 1 Block Diagram of Existing Work

STEP 1: CAPTURED IMAGE AS INPUT

Image are collected and captured information related to betal leaf disease, this disease can be occurs because of environmental, chemical fertilizers or man-made causes. Generally, the captured image will be healthy and affected betal leaf.

STEP 2: RESIZING INTO A FIXED-SIZED IMAGE

The collected image will be processed in order to normalized the lighting conditions and to resized the image. After the resized stage, fixed sized image is obtained.

STEP 3: CONTRAST ENHANCED USING HISTROGRAM EQUALIZATION

Histrogram Equlization is a computer image processing technique used to enhance the contrast in images. This can be performed by the effectively spreading out the most frequent intensity values. Normally, it convert the image to a colour space that has image luminosity of the components.

STEP 4: SEGMENTATION USING GAUSSIAN MIXTURE MODE (GMM)

Gaussian Mixture Mode(GMM) is a flexible tool for image segmentation. GMM can be used to segment the image into pixels into similar segments for further analysis. Image segmentation converts an image into a collection of regions of pixels that are represented by labelled image.

STEP 5: SVM

Support Vector Machine or SVM is one of the most popular Supervised Learning algorithms, which is used for Classification as well as Regression problems. However, primarily, it is used for Classification problems in Machine Learning.The goal of the SVM algorithm is to create the best line or decision boundary that can segregate n-dimensional space into classes so that we can easily put the new data point in the correct category in the future. This best decision boundary is called a hyperplane.SVM chooses the extreme points/vectors that help in creating the hyperplane. These extreme cases are called as support vectors, and hence algorithm is termed as Support Vector Machine. Consider the below diagram in which there are two different categories that are classified using a decision boundary or hyperplane:

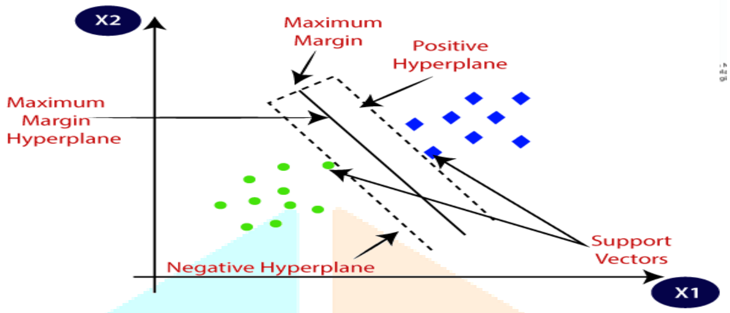


Fig. 2 Representation of SVM Classifier

3.1 RESULTS AND DISCUSSION

A. DATASET

The largest betal vine leaf disease classification dataset is collected and processed which have healthy and affected leaf. 75% of datasets are training and 25% of datasets are tested.

B. EVALUATE THE EXISTING PROTOCOL OF SVM CLASSIFIER

This section gives the performance analysis of accuracy for various images.

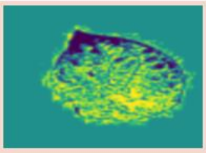
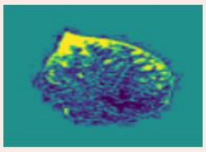
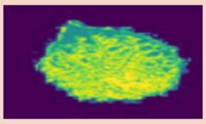
Original image	Resized size	Contract Enhanced Image	Image Segmented - GMM	accuracy
				78.3333
				72.1000
				65.2222

Fig. 3 Results of Existing Work

4. PROPOSED WORK

This section made an attempt to develop betal vine leaf disease detection and classification using ResNet101 and determine the accuracy of various images in the dataset.

A. BLOCK DIAGRAM OF PROPOSED WORK

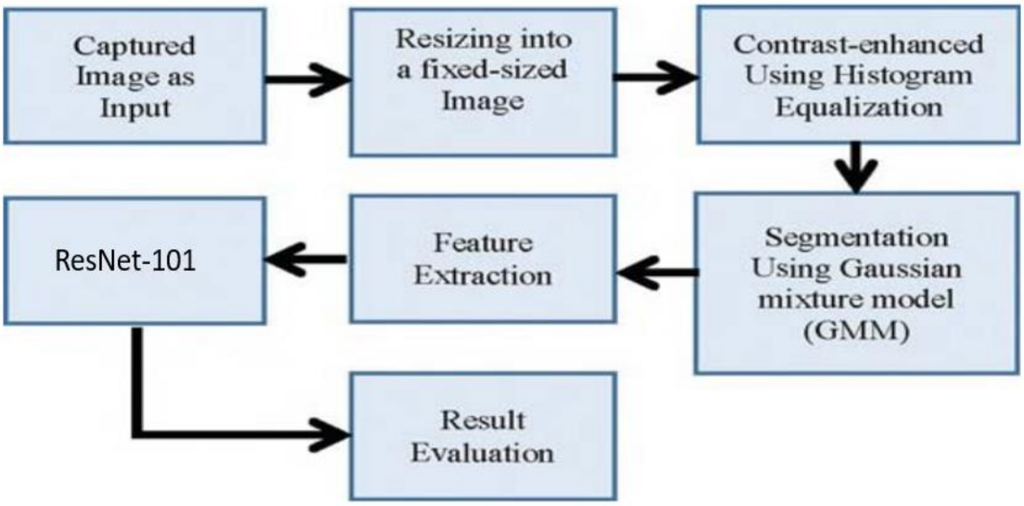


Fig. 4 Block Diagram of proposed work

STEP 1: CAPTURED IMAGE AS INPUT

Image are collected and captured information related to betal leaf disease, this disease can be occurs because of environmental, chemical fertilizers or man-made causes. Generally, the captured image will be healthy and affected betal leaf.

STEP 2: RESIZING INTO A FIXED-SIZED IMAGE

The collected image will be processed in order to normalized the lighting conditions and to resized the image. After the resized stage, fixed sized image is obtained.

STEP 3: CONTRAST ENHANCED USING HISTROGRAM EQUALIZATION

Histrogram Equlization is a computer image processing technique used to enhance the contrast in images. This can be performed by the effectively spreading out the most frequent intensity values. Normally, it convert the image to a colour space that has image luminosity of the components.

STEP 4: SEGMENTATION USING GAUSSIAN MIXTURE MODE (GMM)

Gaussian Mixture Mode(GMM) is a flexible tool for image segmentation. GMM can be used to segment the image into pixels into similar segments for further analysis. Image segmentation converts an image into a collection of regions of pixels that are represented by labelled image.

STEP 5: FEATURE EXTRACTION

Feature Extraction is a process of converting the data into numerical that can be processed. Basically, it helps to increase the accuracy of learned models by extracting features from the input data.

STEP 6: ResNet101

ResNet101 is a deep learning model used for computing vision applications. It is a Convolutional Neural Networks(CNN) architecture designed to support 101 convolutional layers. The architecture of ResNet 101 consists of convolutional layer followed by several blocks of convolutional layers, each containing residual connections. The network also include global average pooling and a fully connected layer for classification. The skip connections technique in ResNet solves the problem of vanishing gradient in deep CNNs by allowing alternate shortcut path for the gradient to flow through. Also, the skip connection helps if any layer hurts the performance of architecture, then it will be skipped by regularization.

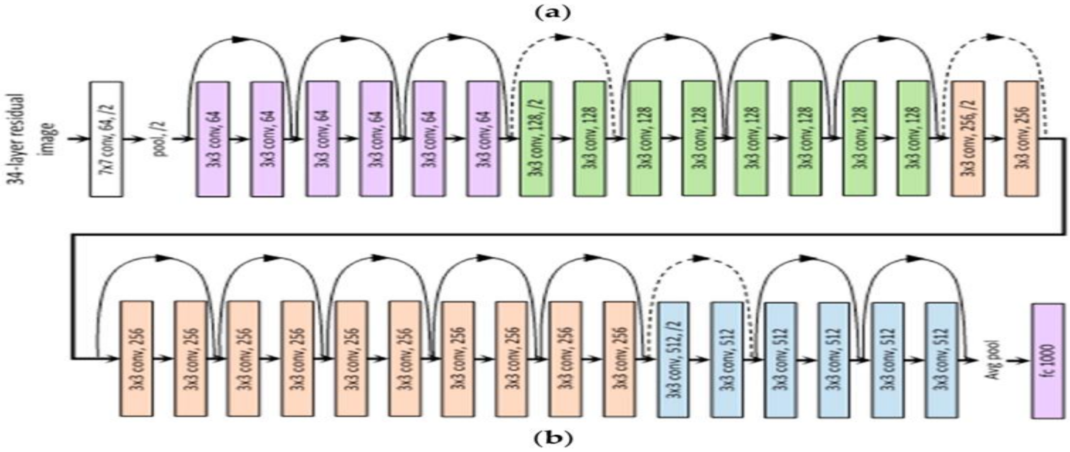


Fig. 5 Architecture of ResNet101

STEP 7: RESULT EVALUTION

The given images are processed in ResNet101 and result are evaluated on the bases of accuracy.

4.1 RESULTS AND DISCUSSION

A. DATASET

The largest betal vine leaf disease classification dataset is collected and processed which have healthy and affected leaf. 75% of datasets are training and 25% of datasets are tested.

B. EVALUATE THE PERFORMANCE OF PROPOSED WORK (ResNet101)

This section shows the performance evaluation of feature extraction and accuracy.

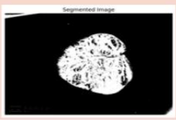
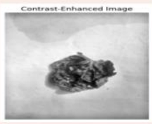
Original image	Resized size	Contract Enhanced Image	Image Segmented - GMM	Feature Extraction	accuracy
				Contrast:[727.9774962] Homogeneity:[0.98888] Dissimilarity:[2.854813] Energy:[0.83798032] Correlation:[0.9609535] ASM:[0.70221102]	85.55%
				Contrast[301.3575208] Homogeneity:[0.99536558] Dissimilarity:[1.1817942] Energy:[0.90670081] Correlation:[0.97325445] ASM:[0.82210635]	83.25%
				Contrast:[892.78349991] Homogeneity:[0.98627036] Dissimilarity:[3.50111176] Energy:[0.76920335] Correlation:[0.96522196] ASM:[0.59167379]	81.23%

Fig. 6 Results of Proposed Work

PARAMETERS	EXISTING WORK	PROPOSED WORK
TRAINING ACCURACY	78.23%	82.23%
TESTING ACCURACY	75.55%	85.55%

Fig. 7 Comparison table of existing and proposed model.

Comparing to the existing work (SVM method) , the proposed method (ResNet101) achieve better accuracy of training accuracy 82.23%, testing accuracy 85.55%.

5. CONCLUSION

In this paper, introduced the basic knowledge of deep learning and presented a comprehensive review of recent research work done in betal vine leaf disease recognition using deep learning. The proposed ResNet101 helps to analyse the healthy and non-healthy diseases by the captured images. It provide feature extraction like contrast, homogeneity, dissimilarity, energy, correlation, ASM and also determine the accuracy.Comparing to the other existing protocol accuracy is high 85.55%. However, any researcher and developers focus on the performance on large dataset and in various conditions.

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