IJESRT: Metanoia 19

ISSN: 2277-9655

# International Journal of Engineering Sciences &Research Technology

(A Peer Reviewed Online Journal)

Impact Factor: 5.164

IJESRT

RESEARCHERID
THOMSON REUTERS

[Metanoia 19]
IC™ Value: 3.00

ISSN: 2277-9655
Impact Factor: 5.164
CODEN: IJESS7

IJESRT

INTERNATIONAL JOURNAL OF ENGINEERING SCIENCES & RESEARCH TECHNOLOGY

# GPLANT: A CLASSIFICATION OF PLANT SPECIES USING GOOGLENET

**Jasitha P[*1] & Divya M[2]**

[*1&2]Dept. of Computer Science and Engineering, AWH Engineering College, Kozhikode, India

**DOI**: 10.5281/zenodo.2629155

## ABSTRACT

The identification and classification of plant species are helpful to prevent the extinction of many plants. Only an expert botanist can classify various plant species correctly. Lack of enough experts and a vast variety of plant species having similar features makes the classification process a laborious and error-prone task. Since proper classification is the primary step to protect and preserve rare plant species, it is necessary to build a simple and error-free classification system. In this paper, we propose an image processing, a computer vision deep learning based method to automate the plant classification system. The performance and computational efficiency of conventional (statistical and hand-crafted) and machine learning approaches are not up to the mark. A deep convolutional neural network outperforms all the other conventional methods. Here we use the transfer learning property of the pre-trained CNN for extracting the features from leaf images. The AlexNet, VGG-16, VGG-19, GoogLeNet, ResNet are such pre-trained networks. Convolutional Neural Network (CNN), GoogLeNet is used here to extract the feature maps. Shape and venation of the leaf image are given priority over other morphological features. Our model tested on different classifiers such as SVM and CNN. The model tested against various standard data sets such as Flavia, DLeaf, and Leaf1. We obtained an accuracy of 99.8% with SVM classifier on Leaf1 data set without cross validation

**KEYWORDS**: Convolutional Neural Network, Deep learning, GoogLeNet.

## 1. INTRODUCTION

The ecological balance on earth is highly determined by plants. Huge variety of plants serves various purposes like food, shelter, medicine etc. The diversity of plant species makes it impossible or not practical for an expert or botanist to manually maintain the details. It is also time-consuming to differentiate or classify them. But it is important to have a knowledge warehouse to carry on the value of different plants from generation to generation. It is also necessary to preserve and conserve them as so many are in the line of extinction. An efficient plant identification can also do a lot in the improvement of food production and drug industries. So it became a need to have accessible, up-to-date tools automating the process of plant species identification and classification.

Plants can be classified based on their fruits, floral parts, stem, branches, and leaves. Since leaves are available in plenty and are present almost throughout the year, a classification based on leaves forms a better approach. Plant leaf classification can be done based on various morphological features. Some of the considerable leaf features are color, shape, texture and venation. No doubt, the shape is a salient feature, however, there are different plant leaves with a similar shape. Leaves' color may vary from season to season. So it is better to contemplate a unique feature like the fingerprint, venation. Since each feature has its own merits and demerits considering maximum possibilities contribute more towards excellence than individual features.
Similar to other image recognition task, the performance of plant identification highly depends on feature extraction methods. In classical techniques hand-crafted feature extractors are necessary. Various machine learning approaches have proved that learned representations are more effective and efficient than features extracted through handcrafted methods. Convolutional Neural Network is exclusively dedicated to image processing. CNN analyses images and identifies features automatically. GoogleNet is one of such pre-trained CNN, we adopted GoogleNet in our model by using transfer learning method.

ISSN: 2277-9655
Impact Factor: 5.164
CODEN: IJESS7

The rest of this paper is developed as follows. Section II briefly describes some previous relevant works on the classification of plant species and different applications of CNN architectures. In Section III, the proposed methodology and solution is described. Section IV presents and discusses the results and finally, Section V concludes this work.

## 2. LITERATURE REVIEW

Hassan Hajjdiab et al. [1] presented a plant recognition technique using the contour of the plant leaves. The distance from the centroid of the leaf contour is cross-correlated in this approach. This method requires minimal user intervention. From the scanned leaf image, the leaf is segmented from the background. Leaf contour is represented as a closed planar curve. Using Green's theorem centroid of the smooth contour is achieved. The feature vector is formulated using Euclidean distance between the centroid and each contour point. The leaf vector of the plant is compared with the leaf vectors of the plants in the database, and the database species with the highest matching score is identified as the species of the given plant leaf. This scale invariant method used only the contour feature in the matching process.

C.H.Arun et al. [2] proposed a texture feature extraction method for identification of medicinal plants. Texture analysis of the leaf images has been done using feature computation. Grey tone spatial dependency matrices(GTSDM), grey textures and Local Binary Pattern(LBP) operators are the features considered here. From the statistical values, a feature vector is generated for each leaf image. The best-suited image is found using the pair-wise distance function. Based on feature values plant leaves are classified using six different classifiers, Stochastic Gradient Descent(SGD), kNearest Neighbour(kNN), Support Vector Machines(SVM), Decision Trees(DT), Extra Trees(ET), Random Forests(RF). Different combinations of the computed features are worked out with few preprocessing filters and without preprocessing. Classification performance of 94.7% is yielded by this method without any preprocessing and on an average of less than 50% with preprocessing. Their data set consist of 250 images 50 images each from 5 leaves.

Sue Han Lee et al. [3] developed a visualization technique based on deconvolutional networks(DN). Deep learning is employed in a bottom-up and top-down manner for plant identification. In the top-down approach, CNN is used to learn unsupervised feature representation. In the bottom-up approach, a deconvolutional network is employed to visualize the learned features. This method avoids the use of the CNN model as a black box solution and provides an insight to researchers on how the algorithm identifies a leaf. Venations of different order have been chosen to uniquely represent each of the plant species. A pre-trained CNN model is used and fine-tuned it using 44 classes of leaf data set. Performance of the CNN model is highly depending on the quantity and the level of diversity of training set. Importance of DN is to identify the unique features on the leaf images that are deemed important to characterize a plant. DN enables to observe the transformation of the features by projecting the feature maps back to the input pixel space. Data set used to evaluate this method is Malayakew with 44 classes of plant leaves. For doing failure analysis two types of data set are considered. D1 consists of full leaves and D2 consist of leaf patches. A performance accuracy of 98.1% is obtained with the D1 data set and 99.5% using D2 data set.

Guillermo L Grinblat et al. [4] proposed a venation based deep Convolutional Neural Network model to identify the plants. Vein segmentation is done with the unconstrained version of Hit or Miss Transform. From the segmented vein pattern, a central patch of 100x100 pixels extracted, which is considered for feature extraction. The classification method and algorithms used here are the Support Vector Machine(SVM), Penalized Discriminant Analysis (PDA) and Random Forests (RF). CNN models of increasing depth from 2 layers to 6 layers were trained. The architecture is the same for all convolutional layers in each model. These models were developed and tested against S1 and S2, two variations of the data set. Performance improved with depth up to the 5-layer model. The 5 layer network outperformed the 6 layer network for S1 and S2 with an average accuracy of 96.9%.

Shitala Prasad et al. [5] presented a medicinal plant leaves classification approach using VGG-16 along with an efficient technique for leaf acquisition. The acquired image was transformed to device independent color space, which is passed to VGG-16 network to compute the feature map. This feature vector is reduced to optimize the

ISSN: 2277-9655
Impact Factor: 5.164
CODEN: IJESS7

classification cost using PCA and the top layer of VGG-16 pre-trained ConvNet architecture is modified to identify the medicinal plants. CNN is used to extract features. An accuracy of 97.6% for l-VGG-16 and 98.2% for l-VGG-16 with PCA methods, using SVM classifier. ImageNet is the considered data set.

Jing Wei Tan et al. [6] proposed a venation based CNN model for leaf classification. They worked on three different models namely D-Leaf, pre-trained AlexNet and Fine-tuned AlexNet for classifying plants. The AlexNet attained an accuracy of 93.26%, D-Leaf model 94.88%, and fine-tuned AlexNet ends with 95.54% accuracy. CNN is used for feature extraction while ANN used for classification. Using the Sobel edge detection algorithm venation of each leaf image was extracted, which forms the input to the considered CNN model. The different layers of pre-trained AlexNet architecture are modified to design the proposed models. Artificial Neural Network (ANN), Support Vector Machines (SVM), k-Nearest Neighbour (kNN), Naive Bayes (NB) and CNN were the classification methods used in this research. ANN outperforms all the methods. Malayakew, D-Leaf, Flavia and Swedish data sets were considered for classification.

Pierre Barre et al. [7] developed a method, LeafNet, to identify the discriminating features from leaf images to identify plant species. Images taken on smartphones and LeafSnap are treated as the input data sets. This model is applied to Flavia and Foliage data sets. The model consists of two convolution layers module and a max pooling layer module arranged alternatively. Such five modules with different filter sizes in each layer are implemented in this model. The highest accuracy of 97.2% is attained on Flavia data set with 32 species.

Azeil Louisse Codizar et al.[8] designed a method named LeaVes to classify different plant species based on the leaf's shape and venation. This system also recognizes plant species from an input leaf image. The method went through three options, detect the edges and view the leaf shape, detect and view leaf veins, and classify the leaf image. The shape is defined by a vector of features extracted via Canny edge detection, Centroid-Radii model and Hu's moment. To extract the veins of the leaf image, it should first be converted to gray-scale. The Morphological opening is applied with a flat, circular structuring element and varying radii to improve the visualization of the veins. The algorithm used for classification is Multilayer Perceptron (MLP), which is a feed-forward neural network. LeaVeS MLP architecture has an input layer with 189 nodes represented the data extracted from the leaf image, one hidden layer with 47 nodes and an output layer containing 32 nodes which represent each species currently stored in the database. Once the prediction process is complete, the user will see a list of matches with their corresponding prediction confidence expressed in probabilities. The adjustable parameters are the number of hidden nodes, the learning rate, and the max error. The system was able to achieve 95% accuracy in classifying the plant species.

Siang Thye Hang et al. [9] proposed several enhancements to the well-known VGG 16-layers Convolutional Neural Network (CNN) model towards open world image classification . The last pooling layer of the VGG 16-layers is replaced with a Spatial Pyramid Pooling layer, enabling the model to accept arbitrary-sized input images. For the activation function, Rectified Linear Unit (ReLU) is replaced with Parametric ReLU in order to increase the adaptability of parameter learning. Introduced an Unseen Category Query Identification algorithm to identify and omit images of the unseen category, thus preventing false classification into predefined categories. If an image belongs to a known category at least one class score should be higher than its corresponding threshold. Image with scores lower than the given threshold for all of the classes will be identified as the image of an unseen category. The dataset used here is LifeCLEF 2016 which contains images of 1000 plant species. It consists of 113204 labeled images and 8000 unlabeled images for evaluation purpose. The average accuracy of 67% is with images of unseen category and 75% without images of an unseen category.

Mostafa Mehdipour Ghazi et al. [10] used various deep convolutional neural networks to identify the plant species captured in a photograph. They carried out a comparative study on popular Convolutional Neural Networks AlexNet, GoogLeNet and VGGNet to determine the parameters affecting the performance of these networks. They evaluated the importance of parameters like iteration size, batch size and the amount of data augmentation in the network's training process. Authors trained the network from scratch and also done training by fine-tuning the parameters. Fine-tuning resulted in higher values of validation accuracy compared to training the model from scratch. Fine-tuned VGGNet outperforms all other networks.

ISSN: 2277-9655
Impact Factor: 5.164
CODEN: IJESS7

B. H. Moran et al. [11] proposed a system to use a Convolutional Neural Network to select regions that may indicate thyroid nodules. The Three popular CNNs were tested, the first one based in the GoogLeNet architecture, a second based in the AlexNet and a third one based in the VGG architecture. GoogLeNet provided the highest accuracy of 86.22%.

Z. Zhu et al. [12] proposed a dual fine-tuning strategy to train the GoogLeNet model. First, the initial model is fine-tuned on WeatherDataset. Second, the structure of GoogLeNet is optimized by truncating operation to reduce the model size of GoogLeNet. And the truncated GoogLeNet is further fine-tuned on WeatherDataset to obtain the final recognition model. This model excels over original GoogLeNet in three aspects of recognition accuracy, recognition speed, and model size.

A number of researches have been taken place in this area of plant species classification using various technologies. Compared to conventional approaches CNN based deep learning approaches yield better performance and high accuracy. Deep learning concept needs to be explored further to introduce an efficient method to address the classification of all types of plants. Standard data sets are also less in number.

## 3. METHODOLOGY AND SOLUTION

CNNs are made up of neurons with learnable weights and biases. ConvNet architectures are build up of mainly three types of layers: Convolutional Layer, Pooling Layer, and Fully-Connected Layer. The convolution layer constitutes a set of independent filters. Each filter is independently convolved with the image and end up with feature maps. Pooling layer operates on each feature map independently. It progressively reduces the spatial size of the representation. Max pooling is the most commonly used approach. In fully connected layer neurons are connected to all activations in the previous layer, Their activations can hence be computed with a matrix multiplication followed by a bias offset.

Various types of CNN architectures are available, which are specially designed to extract features from images and to recognize and classify them. Alex Net, VGGNet, GoogLeNet, ResNet etc. are well known CNN architectures. The ConvNets can be applied to various classification problems in two ways. First, Design and develop a new convNet architecture from the scratch by defining its different layers, filter size, number of filters etc. Second, use the pre-trained convNet as such or by fine-tuning the hyperparameters. Here we apply the second approach using pre-trained GoogLeNet CNN by fine-tuning the hyperparameters in our classification problem.

### *A.* GoogLeNet

GoogLeNet, the winner of the ILSVRC 2014 competition is a 22 layer architecture. It achieved a top-5 error rate of 6.67%, which was very close to the human-level performance. The important component of this deep network is its inception module. GoogLeNet has 9 inception modules. GoogLeNet concentrates on the correlation between nearby pixels in an image.

### *B.* VGGNet

VGGNet, the runner-up at the ILSVRC 2014 competition, consists of 16 convolutional layers and 3 fully-connected layers. Another version of VGGNet, VGG-16 constitute 13 convolutional layers and 3 fully-connected layers.

### *C.* MATLAB

MATLAB is a software package for computation in engineering, science, and applied mathematics. It offers a powerful programming language, excellent graphics, and a wide range of expert knowledge. MATLAB is published by and a trademark of The MathWorks, Inc.

### *D.* DATA SET

The standard data sets Flavia, Dleaf, Leaf1, and LeafSnap are used for training and testing purpose. We randomly divided images in the data set to train data and test data in the ratio 8:2. 3 and 5 fold cross validation is done on these data sets using test data as validation data.

Dleaf, Flavia and Leaf1 data set consist of 1290,1879 and 600 images respectively . Dleaf has 43 classes each having 30 images, Flavia has 32 classes and Leaf1 has 8 classes each having 75 images.

### *E.* PROPOSED SYSTEM

High level representation of the proposed system is given in Fig. 1, which consist of the following steps:

- Image Preprocessing
- Feature Extraction

ISSN: 2277-9655
Impact Factor: 5.164
CODEN: IJESS7

- Classification


Figure 1. ***Abstract Model of Gplant***

Leaf Images in the considered data set can be of varying size and dimensions. These images need to be preprocessed before considering for classification to make it suit the input size of the CNN. For GoogLeNet and VGGNet it is 224x224x3. Through zero padding height and width of each image is made equal, nxn dimension. These images are then resized to 224x224. The resized images are then converted to Gray-scale. An efficient edge detection method, the Sobel edge detection method applied to each image to extract the venation. Since venation is the fingerprint of the leaves this unique feature can be used to identify a plant species. These transformed images are given as the input to the considered CNN.

The venation extracted by Sobel edge detection is given in Fig. 2. The preprocessed venation image is given to the first convolution layer. Since the input image contains only venation patterns, the layer will extract the venation specific features from the image.

The features of the leaf images in the dataset are extracted using the GoogLeNet, pre-trained Convolutional Neural Network. The initial layers of the network extract features like shape, number of branches, number of intersecting points, number of primary, secondary, tertiary veins etc. The subsequent layers extract more features from the feature maps obtained from the previous layers. Depending on the number of filters and filter size in each layer the number of parameters being computed by each layer varies.

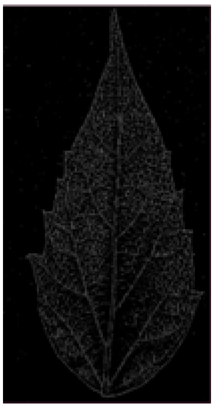

Figure2. ***Venation of a leaf***

As compared to other ConvNets, GoogLeNet works on fewer parameters, because of inception modules. Each inception module contains four 1x1 convolution layers, one 3x3 convolution layer, one 5x5 convolution layer, and a 3x3 max pooling layer. These 1x1 convolution layers mainly contribute towards dimension reduction and thus reducing the number of computation, thereby increases the computational efficiency. In the predefined GoogLeNet architecture, fullyConnectedLayer is customized by assigning new values to WeightLearnRateFactor and BiasLearnRateFactor. Transfer learning is performed by freezing the initial 10 layers. We increased classification accuracy by modifying the training options of the hyperparameters. The hyperparameters like miniBatch size, executionEnvironment, Verbose, maxEpochs, LearnDroprate validationFrequency, validationPatience, initialLearnrate etc. The L2regularization and image augmentation are performed to reduce the overfitting. To avoid classification by just remembering the image position, we performed the rotation and translation in x and y directions. Feature maps are retrieved from the last fully-connected layer and are fed to the classifier.

ISSN: 2277-9655
Impact Factor: 5.164
CODEN: IJESS7

Every convNet has a CNN classifier which takes the trained features from the last fully-connected layer and classifies the test data. The CNN classifier extracts the features maps from the test data and compared with the feature maps of the train data images. Based on the maximum matching CNN performs the classification. To perform the classification using SVM or the other classifiers, the feature maps of both the test and train data are extracted using the trained network. The SVM classifier takes feature maps of the train and test data images as inputs for the classification.

1) Algorithm
Algorithm for the proposed system is given below.
Step1: Consider a predefined data set containing leaf images—Flavia, Dleaf, Leaf1.
Step2: Perform padding to each image to make it equal width and height.
Step3: Resize the images to meet the input size of GoogleNet.ie 224x224.
Step4: Convert the images from RGB to Gray scale.
Step5: Extract the vein architecture of all the leaf samples using Sobel edge detection method.
Step6: Randomly split the data set such that 80% used as training data and 20% as test data.
Step7: Define GoogleNet architecture.
Step8: Perform transfer learning.
Step9: Set training options and train the network with training data.
Step10: Classify the test data using various classifiers.
Step11: Calculate accuracy.

2) Proposed Architecture
A detailed view of the Proposed architecture is given in Fig. 3.

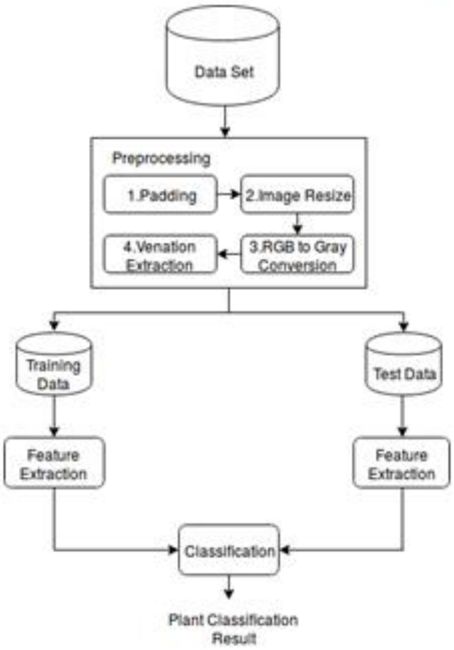


Figure3. ***Proposed Architecture***

## 4. EXPERIMENTAL RESULT

Testing, validation accuracy and testing, training loss are plotted using layer graph. The total classification accuracy and classification accuracy for each class are plotted using confusion matrix. A sample of such a confusion matrix is given in Fig.4 for a small data set consisting of six classes, each class contains 75 images. The diagonal elements of the confusion matrix shows number of images classified correctly in each class.

ISSN: 2277-9655
Impact Factor: 5.164
CODEN: IJESS7

Remaining cells shows the number of misclassified images. One image in the L1One class is misclassified as an image in the L11 class.

GPlant obtained a 5 fold cross-validation accuracy on three publically available data sets, D-Leaf, Flavia and Leaf1 as shown in Table I. Among these Leaf1 data set with SVM classifier gives the highest accuracy of 99.2%.

The accuracy achieved by GPlant is comparable and outperforms the D-Leaf CNN model [6]. D-Leaf model obtained a classification accuracy of 82.75% on D-Leaf data set with SVM classifier. For the same data set and classifier, GPlant achieved an accuracy of 91%. By comparing 5 fold cross-validation accuracies of both the models GPlant outperforms with 95%, whereas D-Leaf has 93.15% on D-Leaf data set. GPlant again outperforms with 96% accuracy on Flavia data set against D-Leaf model, 94.63%, for 5 fold cross-validation.

TABLE I. *5 Fold Cross Validation Accuracy#*

| **Classifier** | **Data Set** | | |
|---|---|---|---|
| | ***DLeaf*** | ***Flavia*** | ***Leaf1*** |
| CNN | 90 | 94 | 98 |
| SVM | 95 | 96.1 | 99.2 |

#. Tesing Accuracy


Figure4. ***Confusion Matrix***

## 5. CONCLUSION

GPlant is a comparable and a good CNN model for plant species classification. Since its error rate is nearer to the human error rate it provides the best classifications compared with other models which are using all types of leaf features. GPlant is using only venation and its related features, bringing the best performance of classification.

## 6. ACKNOWLEDGMENT

We remember with thanks the timely help and constant encouragements induced by our beloved principal Prof. Sabeena M V, head of the department Mr. Gireesh T K, project coordinator Mrs. Shahana T and other faculties of AWH Engineering College, our friends and parents. We express our sense of gratitude to Department of Computer Science & Engineering, AWH Engineering College, for providing us with facilities to complete our work.

ISSN: 2277-9655
Impact Factor: 5.164
CODEN: IJESS7

## REFERENCES

[1] H. Hajjdiab and I. Al Maskari. “Plant species recognition using leaf contours”, In 2011 IEEE International Conference on Imaging Systems and Techniques, pages 306–309, May 2011.
[2] C. H. Arun, W. R. Sam Emmanuel, and D. Christopher Durairaj. “Article:Texture feature extraction for identification of medicinal plants and comparison of different classifiers”, International Journal of Computer Applications, 62(12):1–9, January 2013. Full text available.
[3] S. H. Lee, C. S. Chan, P. Wilkin, and P. Remagnino. “Deep-plant: Plant identification with convolutional neural networks”, In 2015 IEEE International Conference on Image Processing (ICIP) , pages 452–456, Sept 2015.
[4] Guillermo L. Grinblat, Lucas C. Uzal, Monica G. Larese, and Pablo M.Granitto. “Deep learning for plant identification using vein morphological patterns”.
[5] S. Prasad and P. P. Singh. “Medicinal plant leaf information extraction using deep features”. In TENCON 2017 - 2017 IEEE Region 10 Conference, pages 2722–2726, Nov 2017, 127:418 – 424, 2016.
[6] J. W. Tan, S. Chang, S. Binti Abdul Kareem, H. J. Yap, and K. Yong. “Deep learning for plant species classification using leaf vein morphometric”, Pages 1–1, 2018.
[7] Pierre Barre, Ben C. Stover, Kai F. Muller, and Volker Steinhage. “Leafnet: A computer vision system for automatic plant species identification”, Ecological Informatics, 40:50 – 56, 2017.
[8] A. L. Codizar and G. Solano. “Plant leaf recognition by venation and shape using artificial neural networks”, In 2016 7th International Conference on Information, Intelligence, Systems Applications (IISA), pages 1–4, July 2016.
[9] S. T. Hang and M. Aono. “Open world plant image identification based on convolutional neural network”, In 2016 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA) , pages 1–4, Dec 2016.
[10] Mostafa Mehdipour Ghazi, Berrin Yanikoglu, and Erchan Aptoula. “Plant identification using deep neural networks via optimization of transfer learning parameters”, Neurocomputing, 235:228 – 235, 2017.
[11] B. H. Moran, M and Conci, A and R. Gonzalez, J and S. Araujo, A and G. Fiirst, W and P.Damiao, Charbel and A. B. Lima, Giovanna and A. da Cruz Filho, Rubens. “Identificationof thyroid nodules in infrared images by convolutional neural networks”, Pages 1–7, 07 2018.
[12] Z. Zhu and J. Li and L. Zhuo and J. Zhang. “Extreme weather recognition using a novelfine-tuning strategy and optimized googlenet”, In2017 International Conference on DigitalImage Computing: Techniques and Applications (DICTA), pages 1–7, Nov 2017.