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A Literature Review on Citrus Fruits and Leaves diseases detection using Deep Neural Network model

C.Vinothini
Associate Professor
Dept. of CSE
Dayananda Sagar College of Engineering
Bangalore, India.
vinothini-cs@dayanandasagar.edu

Aditi Anand Huralikoppi
Dept. of CSE
Dayananda Sagar College of Engineering
Bangalore, India
ah.aditi@gmail.com

Kunche Nithyasree Royal
Dept. of CSE
Dayananda Sagar College of Engineering
Bangalore, India.
kunchenithyaroyal@gmail.com

Guduru Rama Koushika
Dept.of CSE
Dayananda Sagar College of Engineering
Bangalore, India
gudurukousi55@gmail.com

Koppala Jyoshna
Dept.of CSE
Dayananda Sagar College of Engineering
Bangalore, India
jyoshnakoppala3@gmail.com

Abstract: In Agriculture, decline in the yield of citrus fruits is mainly caused by diseases occurring in citrus fruits and leaves. Early detection of diseases involves usage of deep learning strategies by designing an automated detection system with a convolutional neural network (CNN) model. The diseased citrus fruits and leaves of Scab, Black Spot, Canker, Melanose, and Greening are separated from healthy leaves by combining and fusing several layers. The main purpose is to build a model which identifies the disease and allocates the corresponding disease class to the image. Deep learning classifiers uses many layers with optimal parameter set whereas classical feature representation methods are employed by Machine Learning classifiers to classify images.

Index Terms- **CNN, Deep Learning methods, Citrus fruit and leaves diseases detection**

I. INTRODUCTION

Research in agriculture plays a pivotal role in raising food production, improving quality of food while reducing costs and enhancing profitability. Citrus diseases like Melanose, Black Spot, Canker, Greening and Scab are a cause of concern among farmers. Citrus trees can get Canker, which is primarily located on the leaves or fruit and is extremely contagious. We decided Deep Learning techniques to solve the problem of identifying five types of citrus diseases because they have demonstrated promising outcomes in several deep learning problems. The application of convolutional neural network model aims to differentiate amongst healthy and diseased citrus leaves and fruits. By combining multiple layers, the CNN model captures complementing discriminative characteristics.

Contribution: We have surveyed the existing research in the areas of detection of citrus fruits and leaves disease detection. We have examined the different methodologies used in the respective solutions in the works and have put forward them in a lucid manner.

Paper Organization: The organization of the paper is as follows. Section II is the survey of the literary research papers. Section III is the implementation of the suggested model from us. Section IV is the conclusion of the survey work. Section V encloses the reference.

II. LITERATURE SURVEY

Detection of HLB disease based on automatic ROI segmentation and transfer training [1]:
Huanglongbing (HLB) disease affects the citrus production which results in a huge economic loss to the farmers. Huanglongbing is detected using convolutional neural networks which is primarily based on computer-vision systems. The system should be able to distinguish Huanglongbing and the abnormalities in citrus. The CNN architectures have convolution kernels and pooling layers which extract feature vectors [11]. As depth of CNN increases, the dimensions of element maps lower to activate finer functions. A connected layer along with a softmax activation classifies the images [12]. To train CNN

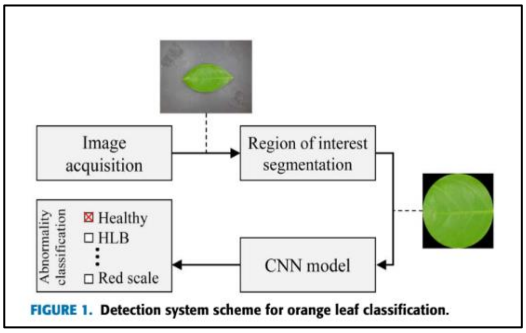


Figure 1: Orange leaf disease detection [1].

based systems there is difficulty in collecting large datasets. The CNNs which use small datasets increase the trainable parameters to be considered in CNN. This character of CNN leads to overfitting in case of small dataset which is solved by transfer learning from pre-trained CNN's. The CNNs which are already pre-trained tuned to differentiate Huanglongbing, abnormalities and healthy cases of citrus. In Transfer learning large datasets is used for training the CNN model and fine tuning is used to transfer learned parameters to smaller datasets. Also, a hand-crafted feature based conventional method was evaluated. VGGNet shows the highest accuracy while classifying the disease as it is the deepest series network. VGGNet has more network depth and higher trainable parameters. In series networks, an increase in network depth increases the training computational cost increases because of the increase in trainable parameters.

A MobileNet V2 model based on Improved Whale Control Entropy Optimization for citrus disease identification [2]: This study involves a single stream convolution neural network architecture with improved optimization is used for classification of citrus fruits and leaves diseases. Data augmentation is used for increasing the number of samples for training which is based on four operations- Improving brightness, pixel intensity adjustment, shadow removal and improving local contrast by flipping, rotating [13]. This process gives better

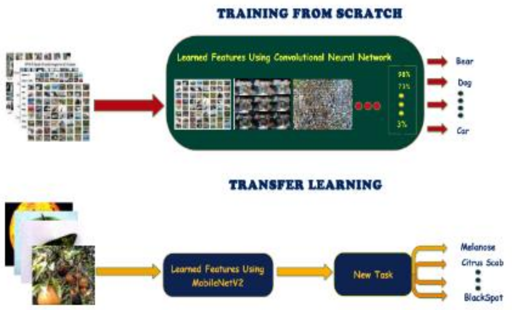
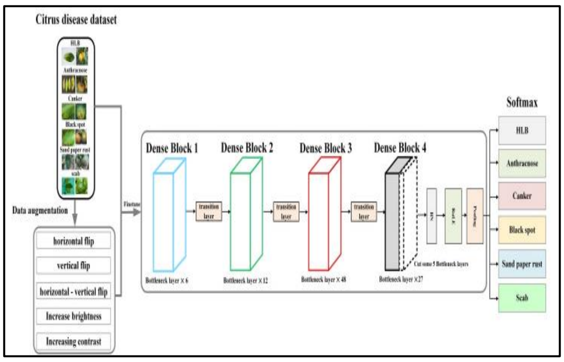


Figure 2: MobileNet V2 deep model [2].

training for the selected CNN model. MobileNet-V2[14] CNN model is introduced and by employing transfer learning concepts they are trained on a newly augmented dataset.

Deep features are extracted as a feature vector from the newly trained model and with the help of the analysis of features extracted which contain some unnecessary information. Hence, Whale Optimization Algorithm is used which is improved. Finally, classification is done through the best selected features using a neural network to compare performance with the other classifiers such as Gaussian Naive Bayes, SVM (linear and quadratic) and fine tree and then results are calculated. To store and collect information, MobileNet V2 has a new component known as the inverted residual [15]. The main advantage of this is the proposed architecture had a better performance compared with the other methods in terms of time and accuracy. The major findings from results are improved learning capability of a CNN model and best feature selection reduces computational time and helps maintaining accuracy.

A simplified DenseNet framework for detection of citrus disease [3]:



Architecture of the simplified DenseNet training model [3]

Development in communication technology is driving newer advancements in broader areas. Mobile Service Computing has played a key role in always accessing services through mobile applications. This research intends to prepare a dataset of images of six types of citrus diseases with professional support and build a simplified densely connected convolutional neural networks (DenseNet) to provide a clear diagnosis system for disease classification. Through the WeChat applet, this system is implemented on mobile devices where images are uploaded by users which displays results and suggestions. The simplification of the structure of DenseNet also reduces the consumption of prediction time. This system provides feedback on the type of citrus disease and suggests disease-specific treatment plans to help prevent and treat diseases. The architecture of the simplified DenseNet is as follows: DenseNet layers are mostly removed to reduce overfitting and prediction consumption. The DenseNet 201 is made up of 4 different types of dense blocks and a transition layer that connects every dense block. The bottleneck layers of 6, 12, 48 and 32 layers make up the dense block. The bottleneck layer is made up of BN-ReLU-Conv(1×1)-BN-ReLU-Conv(1x1), [16]. The 5 bottleneck layers in the final Dense Block are removed and Batch Normalization, Activation function, Average pooling and Softmax layers are added which make up the simplified DenseNet. To fine-tune the simplified DenseNet, the data augmentation and dataset original dataset are used. Through this approach, barriers between the farmers and specialists are reduced and thereby helps the farmers in early detection of citrus diseases and treatment. Deep learning features are more representative of image content than traditional manual features and improves recognition efficiency. As the depth of the network increases, overfitting can occur and reduce the effectiveness of the classification.

Classification and disease detection of citrus fruits based on Otsu segmentation, Inception Resnet V2 and Random Forest Classifier [4]: They presented an automatic citrus disease detection involving Otsu-based segmentation process and Inception v2 feature extraction based ResNet. Random Forest algorithm is used as a classifier to classify and differentiate various kinds of citrus diseases. The first step is pre-processing where the image quality

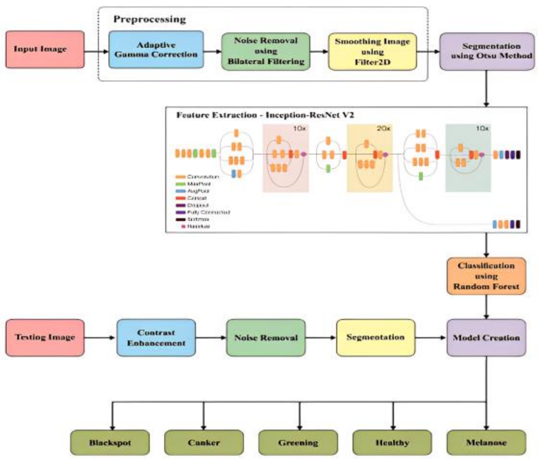


Figure 4: Otsu-based segmentation process with Inception ResNet V2 model [4].

is improved. Pre-processing is done at two main stages: Contrast Enhancement [17], where adaptive gamma correction (AGC) techniques are employed and Reduction of Noise, where Bilateral Filters (BF) is used to remove outliers in the image. The second step is segmentation of images by Otsu model which is used in numerous image processing for threshold-based image segmentation and conversion of grey scale images to binary images. To obtain an efficient model, the class probabilities are determined iteratively. The third step involves feature extraction by Inception ResNet V2 model, where the first layers are trained in extraction of low-level attributes comprising of edges, lines, and dots. The mid-level features like sharpness, shadowing of images by the deeper network layers. The precision-level features, that is, detection of disease in the image is done by deepest layer. A filter expansion layer is used after Inception block to increase the filter bank dimension before adding it to map the input depth. The extracted features of the images are classified into different classes by Random Forest classifier using Decision Trees from forests. The first step involves constructing a tree by arbitrarily choosing unique instances of identical sizes using partial training. Cross validation models are used for residual instances. GINI index calculates the impurities of predefined parameters.

A Faster R-CNN based two-stage convolutional neural network and ResNet 101 for citrus disease detection and classification [5]:

In this paper, they proposed an advanced classification and detection method to detect the disease using three most popular citrus diseases: Black spot, Huanglongbing and Canker. A two-stage deep Convolution Neural Network model is proposed using the leaf images and detecting the plant disease for classification of citrus diseases. This Faster R-CNN [18] based model consists of ResNet 101 feature extractor and finding the areas of the leaf with most disease affected regions using the Regional Proposed network [19]. This helps reduce the training

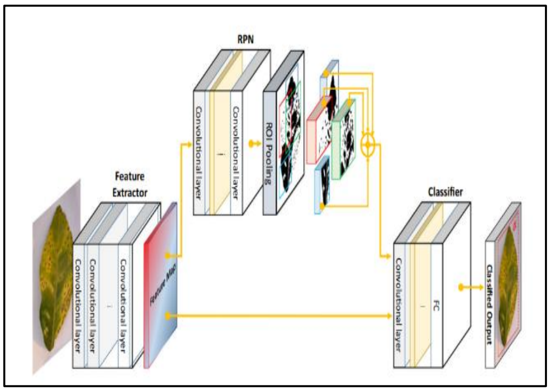


Figure 5: Faster R-CNN convolutional neural network model [5]

overhead by sharing the features between the RPN and the classifier. A loss function was used to compute the average loss obtained from the RPN model and classifier. The specified regions by the RPN network are not treated the same and the loss function of the RPN network represents the result of the model. Therefore, the result of the model is much contributed by the areas having larger probability of having disease patterns. The model gives the best performance for the reason of having RPN and the classifier which helps in the classification of target regions. This leads to decrease in false positives and these are caused by other portions of the image with less contribution to the target class. The loss function should be changed to determine the superiority of this model over conventional faster RCNN.

Survey on different computational methods used in citrus leaf disease detection [6]:

This study employed the outline of different image processing methods for detection of plant diseases. The stages of detection include extraction of features, pre-processing, classification, and segmentation. Through this survey, we came to know that precision of segmentation [20] has increased by the image processing strategies. Classification suitability can be controlled through the selection of five classification algorithms which are of prime importance. Finally, a model with hyperparameters is constructed with the algorithm having the maximum and excellent efficiency. The five techniques used in the analysis are K-NN, Naive Bayes, Artificial Neural Networks, Multi SVM and Random Forest [21]. K-Means clustering technique is being used as the most crucial strategy for segmentation of images. Different techniques are used to extract different features of the leaf like texture, color, shape, etc. but texture features provide good results. Texture of a picture is the one of the most important characteristics for the disease depiction, while K-NN and SVM use these characteristics.

A transfer learning VGGNet based model for detecting level of severity of disease in citrus fruits [7]:

The version to detect all the affected regions and the severity stages of the citrus fruit disorder majorly consist of 5 modules. The gathering of images of citrus fruit happens in the first module. Professional knowledge is applied to label unhealthy and healthy images in the second module. Labelling defines the procedure of presenting annotation to the graphical pixel and used to label the bounding field for detection of item. Pixel annotations are saved as XML documents in Pascal VOC form. Regions of proposal which are not dependent of the class are produced by object detection and segmentation based on graph in the third module. The calculation of similarity between the regions is calculated by grouping of the most similar regions. A feature map of fixed length for each region is extracted by a transfer learning-based CNN network in the fourth module. The severity of the disease is obtained by the multi-class sequential CNN with a softmax function in the last module. The algorithm is as follows: The coloured photograph (Img) is used as an input. Annotation of the photograph, Annotate (Img) takes place wherein BoundingBox (Img) is used to form coordinates of outline of the regions that are affected and the Annotate (Img) feature is utilized to generate and procure the annotated photograph as XML report for every photograph. Creating item for every category (i.e., for low, healthy, excessive, and medium), pre-processing of image by extracting the image url and image name. LBP is used in computing the texture gradient of the image. A colour histogram having COLOUR_CHANNELS (3)* containers with 25 containers is used to extract HSV for an image. The histogram parameters are augmented with regions and the region proposal is returned. Computing the similarity Sim(rα,rβ) = colour similarity Simcolour (rα,rβ)+ texture similarity Sim texture (rα,rβ)+ length similarity Sim length rα,rβ+ .Calculate IOU for areas.

AUTHOR	ALGORITHM/METHODOLOGY	ADVANTAGES	DISADVANTAGES
W. Gomez-Flores, J. Jose Garza-Saldana [1]	AlexNet, VGGNet (Series Networks) and ResNet, GoogLeNet, Inception-V3(DAG) are used. DAG networks have deeper layers and less parameters than Series networks, enabling efficient training of deep CNN models.	VGGNet shows the highest accuracy while classifying the disease as it is the deepest series network. VGGNet has more network depth and higher trainable parameters.	In series networks, an increase in network depth increases the training computational cost increases because of the increase in trainable parameters.
M. Hassam, M. Attique Khani [2]	Usage of Modified MobileNet V2 model with improved Whale Optimization Algorithm controlled entropy through depth wise separable convolutions techniques	By modifying the MobileNet V2, increase in training data improves the CNN's model learning capacity. This gives enhanced recognition accuracy.	It must be implemented on larger datasets.
W. Pan, J. Qin [3]	Simplified DenseNet-201 architecture consisting of four Dense Blocks and one transition layer.	DenseNet reduces the vanishing-gradient problem, strengthens propagation of features and reuses features which reduces number of parameters.	Less training samples might result in poor classification results.
S. Farhana Syed-Ab-Rahman [5]	A Faster R-CNN based two stage deep convolutional neural network	The model gives very low standard deviation. This represents robustness of the network. It also gives good accuracy when trained with smaller number of samples	There is a drop in accuracy while classifying citrus black spot because there is a substantial change in the spot size of the diseased leaf.

An improvised AlexNet and Deep Convolution Generative Adversarial Network for canker classification on small dataset. [8]:

This survey is an improvement over the traditional method of citrus canker disease detection where there is poor availability of training images. The survey involves expanding the dataset through 2 techniques: feature augmentation and objective breakdown optimization. A deep convolutional generative adversarial network aids in the positive sample distribution. Different layers of the model are updated using attributes at the optimum level. Our approach involves several steps:

A. Magnification of features: Feature magnification is a process to rectify the shortage of positive training samples by building a generative model resulting in production of real-time artificial samples which share a similarity to the genuine samples. The problem of overfitting in the discriminator network makes it difficult in updating the generator due to the restrictions of the loss function. Owing to this, the original model is modified. Each image sample was data augmented before the learning of genuine samples based on statistical distribution. Horizontal and Vertical flipping of samples along with sample rotation by 0◦, 90◦, 180◦ , and 270◦ of four other copies is precisely done for every image sample in the dataset. The model is based on a customized architecture implemented on DCGAN between convolutional and batch normalization called as mute layers. A mute layer excludes a certain number of signals during validation and training whereas the dropout layer excludes certain signals during training and skips during validation.

B. Optimization objective: AlexNet model proves as an added advantage over the traditional method of image classification by considering the traits involved. To overcome the problem of slow de novo training of AlexNet the weights available publicly are pretrained on ImageNet, initialized and the weights are updated on fully connected layers resulting in all other parameters unchanged. The problem of occasional overfitting can be solved by incorporating Siamese training arising from samples of different class labels which are in proximity. The model is divided into two parts with the use of suitable training to specific parts. A latent layer l based on a specific hyperparameter divides the two parts. The preceding layers reduce the calculated Siamese loss and the succeeding layer lowers the cross entropy calculated against output layer ground truths.

III IMPLEMENTATION

The architecture of the system we are planning to implement is as follows: A Multilayer Convolutional Neural Network is used for the classification of citrus fruits and leaves affected with five different diseases, namely, Citrus Canker, Blackspot, Melanose, Greening and Scab. The system differentiates between diseased and healthy citrus leaves and fruits. There are five modules in the suggested architecture (i) input image preprocessing (ii) CNN layer-1 (iii) CNN layer-2 (iv) Flatten Layer (v) Classification Layer

(i)Input Image Preprocessing: The images from the dataset are pre-processed using the Keras Image Preprocessing, ImageDataGenerator class and API. The class includes methods like data normalization and scaling of pixels. The input image is a pixel array which occupies the screen's width and height. An input shape parameter is employed to construct the input image matrix which is three-dimensional consisting of red, blue, green layers for colored images.

(ii)First CNN Layer: Extraction of features is done in this layer. Learnable filters (small matrices) are convolved with the input image matrix to produce the feature matrix. A function map is generated by applying a filter matrix to the image matrix through convolution operation. Rectified Linear Unit (ReLU) is used as the activation function in this layer which signifies the CNN model's non-linearity.

(iii)First Maxpooling Layer: Also known as the subsampling layer, it reduces the size of our feature map.

(iv)Second CNN Layer: It captures the output of the Maxpooling layer, namely, the pooled functional matrix and derives high

level attributes.

(v)Second Maxpooling Layer: This layer decreases the scale of the matrix.

(vi)Flatten Layer: This layer transforms pooled feature matrix into a vector(column) Classification Layer: The dense layer having multiple neurons is fed into the activation functions. Softmax activation function is used which assigns the probabilities for the various categories of diseases considered. The category with the highest probability is the disease detected in the input image.

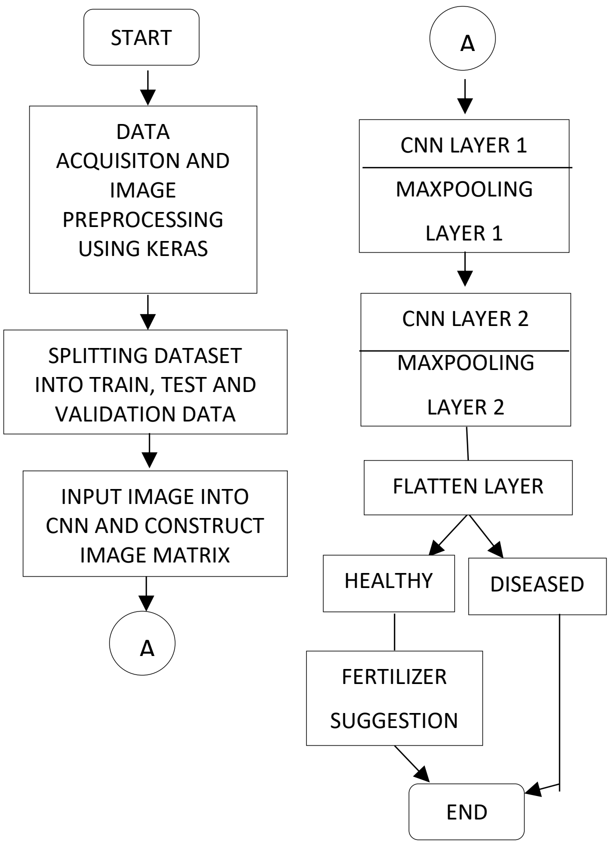


Figure 7: Architecture of the model considered for implementation

Thus, the suggested CNN model aims to distinguish between healthy and diseased citrus fruits and leaves through images. The accuracy of the model is found by using metrics like precision, recall and f -score.

IV CONCLUSION

The CNN-based citrus fruits and leaves disease detection model differentiates and identifies healthy citrus fruits/leaves from unhealthy diseased citrus fruits and leaves. The CNN model successfully tackles the problem of disease classification from citrus fruit/leaf images. There are 2 convolutional layers used where the first layer extracts low-level basic attributes from the image, and the second layer extracts high-level advanced attributes which help in classifying the images into classes such as healthy, greening, canker, scab, Blackspot and Melanose. After the disease is detected for citrus fruit/leaf, the fertilizer that can reduce the effect of that disease is suggested. The traditional methods of image processing use several steps and handcrafted features to classify images whereas the deep learning methods use end-to-end automatic feature extraction through neural networks.

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