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Early Detection of Rice Leaf Diseases using Efficient U-Net and Deep Learning

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Abstract

Rice is considered one the most important plants globally because it is a source of food for over half the world's population. Like other plants, rice is susceptible to diseases that may affect the quantity and quality of produce. Early detection of these diseases can positively affect the harvest, and thus farmers would have to be knowledgeable about the various disease and how to identify them visually. In this paper, a Deep Learning technique for the accurate detection and classification of rice leaf disease is proposed. The residual attention based Efficient Net-U-Net is proposed for the process of segmentation. For the detection and classification of the rice leaf disease, Convolutional Neural Network (CNN) is proposed. The performance of the proposed work is evaluated in terms of accuracy, precision, recall and F1 score. The proposed work obtains the highest accuracy of 89.35%,

Introduction

Plants and fruits are the primary source of energy for the human as well as animals. Leaves ofvarious plants and herbs are useful to mankind due to their medicinal attributes. Countries likeAsia and Africa where over 50% of population depends on agriculture production for employment, export earnings and food security [1].Paddy is one of the essential crops worldwide, considering its impact on the global food market. The demand for food items such as rice is increased more than ever with a growing population. The environmental impacts (i.e., soil, weather) on the cultivation of paddy have a significant contribution to the production rate of rice throughout the world [2]. However, the next significant influence on increasing production is the effective management of paddy diseases and pests. Controlling the diseases spread over crops and ensuring the minimization of production loss becomes challenging. However, the safety of food remains challenging owing to factors such as climatic changes, a decline in pollinators, plant diseases, and others [3].

Over the past decades, plant diseases are identified by experts with a bare eye. This approach shows a lack of accuracy and unavailability of experts in rural areas. Early detection of diseases allows taking preventive measures against pathogens. Automated classification of plant diseases using leaf images can detect the possibility of diseases more accurately [4-6]. Even though automated classification is considered as one of the accurate methods to classify the disease, few complications occur due to inter-class similarities of plant and extrinsic factors including variations in image background, illumination, color, pose, and occlusion. Computer vision, machine learning, image processing, and deep learning techniques turn out to be efficient ways to detect plant disease at the early stage and continuous monitoring of plant health conditions. The contribution of the work is,

- To detect the plant disease automatically,proposed the deep learning techniques which efficiently detects the diseases.
- To implement fusion based deep learning model/technique for plant diseasedetection and segmentation.
- For segmentation EfficientNet with U-Net is proposed.
- For plant disease detection and classification, CNN is proposed.

The structure of the work is organized as, Section 1 introduces the work, Section 2 describes the related works, Section 3 presented the methodology of the work, Section 4 discusses the results and Section 5 concludes the work.

Related works

Murk et al. (2020) proposed a deep learning-based model named plant disease detector. The model is able to detect several diseases from plants using pictures of their leaves.First of all, augmentation is applied on the dataset to increase the sample size. Later Convolution Neural Network (CNN) is used with multiple convolutions and pooling layers. Plant Village dataset is used to train the model. After training the model, it is tested properly to validate the results.Yong et al. (2020) proposed the convolution neural network which is used to automatically identify crop diseases. In this paper, the Inception-ResNet-v2 model is used for training. The cross-layer direct edge and multi-layer convolution in the residual network unit to the model After the combined convolution operation is completed, it is activated by the connection into the ReLu function.Yanet al. (2020) proposed a mathematical model of plant disease detection and recognition based on deep learning, which improves accuracy, generality, and training efficiency. Firstly, the region proposal network (RPN) is utilized to recognize and localize the leaves in complex surroundings. Then, images segmented based on the results of RPN algorithm contain the feature of symptoms through Chan–Vese (CV) algorithm. Finally, the segmented leaves are input into the transfer learning model and trained by the dataset of diseased leaves under simple background.

Chenet al. (2020) studied the deep learning approach for solving the task since it has shown outstanding performance in image processing and classification problem. Combined the advantages of both, the DenseNet pre-trained on ImageNet and Inception module were selected to be used in the network, and this approach presents a superior performance with respect to other state-of-the-art methods. It achieves an average predicting accuracy of no less than 94.07% in the public dataset.A faster region-based convolutional neural network (Faster R-CNN) was employed for the real-time detection of rice leaf diseases in (Bari et al. (2021). The Faster R-CNN algorithm introduces advanced RPN architecture that addresses the object location very precisely to generate candidate regions. The robustness of the Faster R-CNN model is enhanced by training the model with publicly available online and own real-field rice leaf datasets. The proposed deep-learning-based approach was observed to be effective in the automatic diagnosis of three discriminative rice leaf diseases including rice blast, brown spot, and hispa with an accuracy of 98.09%, 98.85%, and 99.17% respectively.

An improved plant disease-recognition model based on the original YOLOv5 network model was established in (Chen et al. (2022). First, a new Involution Bottleneck module was used to reduce the numbers of parameters and calculations, and to capture long-distance information in the space. Second, an SE module was added to improve the sensitivity of the model to channel features. Finally, the loss function ‘Generalized Intersection over Union’ was changed to ‘Efficient Intersection over Union’ to address the former’s degeneration into ‘Intersection over Union’. These proposed methods were used to improve the target recognition effect of the network model.Sue et al. (2020) developed a new technique based on a Recurrent Neural Network (RNN) to automatically locate infected regions and extract relevant features for disease classification. RNN-based approach is more robust and has a greater ability to generalize to unseen infected crop species as well as to different plant disease domain images compared to classical CNN approaches.RNN is capable of accurately locating infectious diseases in plants.Saleem et al. (2020) proposed the deep learning-based comparative evaluation for the classification of plant disease in two steps. Firstly, the best convolutional neural network (CNN) was obtained by conducting a comparative analysis among well-known CNN architectures along with modified and cascaded/hybrid versions of some of the DL models. Secondly, the performance of the best-obtained model was attempted to improve by training through various deep learning optimizers.

Methodology

In this paper, paddy leaf disease identification method based on a deep learning fusion model is proposed. First, the image dataset is established, and the image noise in the dataset is filtered out to increase the efficiency. Next, the processed images are provided as input into disease detection model for training. The flow of the proposed work is shown in Figure 1.The proposed methodology started with image preprocessing, argumentation, and segmentation to divide an image into multiple tiles, and tiles were further used to extract disease segments. The segmented images are further used to train DL model.

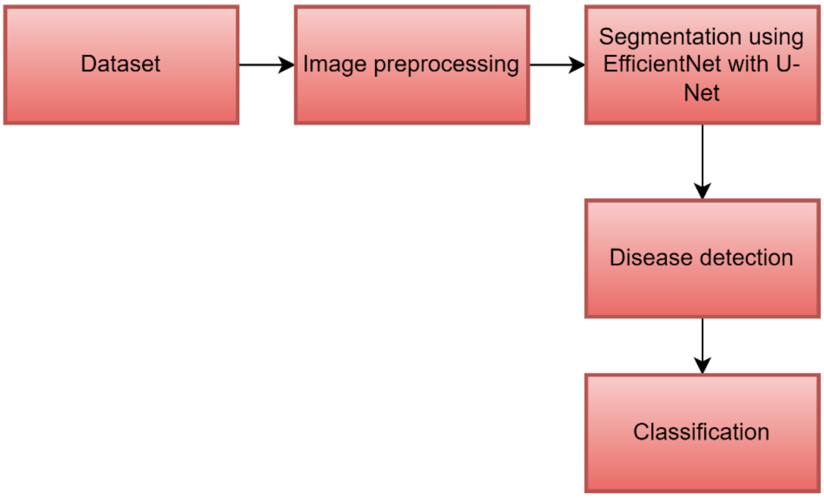

Figure 1 Flow of the work

Dataset

The dataset contained 1500 paddy images comprising 1000 pictures for training data and 500 for testing and validating data. The data were required to train, test, and validate object recognition tasks. The dataset consists of four classes: three paddy leaves that were infected and one type of paddy leaf that was healthy. Figure 2 and Table 1 indicate the four classes of paddy leaves.

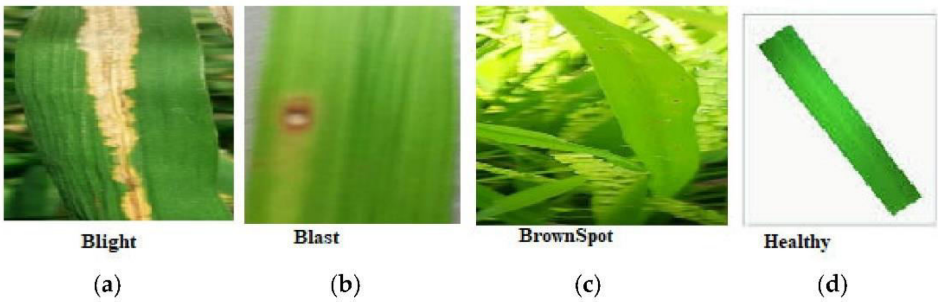

Figure 2. Four classes of the paddy leaves

Table 1. Paddy leaf disease dataset classes

Class	Count of Images	Training Images	Testing/Validation Images
Blight	300	250	50
Blast	365	300	65
Brown spot	335	270	65
Healthy	500	400	100

Image preprocessing

Data preprocessing is important task in any computer vision-based system. To get precise results, somebackground noise should be removed before extraction of features. So first the RGBimage is converted to greyscale and then Gaussian filter is used for smoothening of theimage. Then to binaries the image, Otsu's thresholding algorithm is implemented. By using contours, area of the leaf and perimeter of the leaf is calculated.Contours are the line that joins all the points along the edges of objects having samecolor or intensity. Mean and standard deviation of each channel in RGB image is alsoestimated.

Segmentation using Efficient-U-Net

Efficient-U-Net is a proposed network that comprises of an encoder and a decoder. Given the limited computer resources, we use a modified EfficientNetB4 as the encoder. The encoder is made up of nine stages: a 3x3 convolutional layer, 32 mobile reversed bottleneck convolutional (MBConv) structures, and an 11 convolutional layer. The decoder is made up of five up sampling processes and a sequence of convolution operations. The encoder's retrieved features are then restored to the original picture size, and the segmentation results are obtained. To improve the accuracy of the segmented crack, we add an attention gate to the skip connection to limit noise response and focus on certain characteristics.The insertion of the residual structure can deepen the network. After each convolution, the residual block performs batch normalization (BN) and ReLU activation. The use of batch normalization can eliminate gradient diffusion and vanishment and speed up network convergence. Then, using ReLU, execute non-linear processing to increase the network's non-linear expression capabilities.

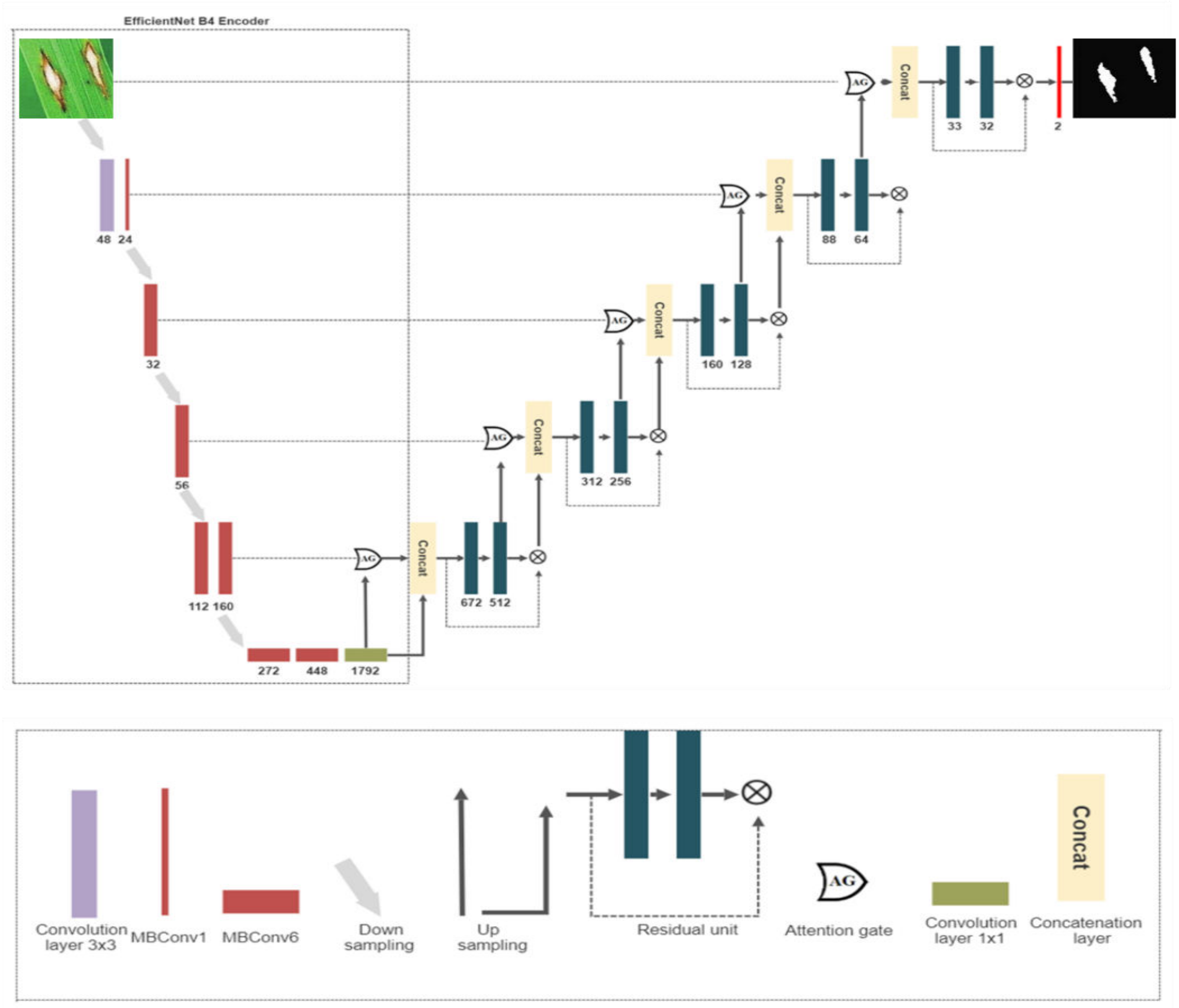

Figure 3 Architecture of Efficient-U-Net

Classification using CNN

Convolutional Layer

The convolutional layer is important in a deep neural network that is used to extract high-level and low-level features from the input image. This layer uses convolution operation to extract features from the input. The initial layers extract low-level features, and the layers at the end extract high-level features from the input. In this paper, the dataset contains 256 × 256 images, and a 3 × 3 filter is used for convolution operation to extract image features. In this arrangement, fifteen convolution filters with a 3 × 3 kernel size are used with the activation function (ReLu). This function provides the capability to learn more complex and complicated features from the input. This rectifies the vanishing gradient problem.
The convolution operation is defined as a binary operation (represented by the symbol '*') between two real-valued functions (for example, *A* and *B*). In the continuous domain, it can be mathematically defined as in Equation (1).

Each characteristic of the map is intertwined with numerous input attributes. For example, the following equations apply to input x of the i^{th} convolution layer:

$h_{ic} = F(A_i * B)$ (1)
where F is a function of activation, B is convolution, and A is a layer kernel of convolution. The number of kernel convolutions on a single layer is = $[A_{i1}, A_{i2}, \dots, A_{ik}]$.

Pooling Layer

A huge number of convolution layers will increase the network parameter exponentially, which can be reduced using max pooling layers because the convolution layer generates a huge feature map that can be reduced with pooling layers. The pooling layer extracts potential features from the feature map. In this layer, the maximum value is taken from the available feature map. The pooling layer is also used to minimize dimensions and can aid translation invariantly. To begin with, region R has max pooling that can be defined as average pooling.

$M_p = max_{i \in R_j}(x_i)$ (2)

Fully Connected Layer

After the max pooling layer, the detection and classification are performed in the FC layer. For evading the overfitting problems, masking probability with dropout is subjected to the penultimate layer. The final classification is portrayed as,

$\hat{t} = \mu(x_I(h_s \otimes I) + w_I$ (3)

Thus, the classified outcome is designated as Qc, which indicates either bacterial blight, leaf blast, brown spot or healthy.

Results and discussion

The entire experiment setup has been accomplished in Python with Co-Lab. The karas neural network libraries were used to construct, compile, and evaluate the model. The experiment was performed on Google Co-lab to avail Graphical Processing Unit (GPU) recourses. The experiment was performed in cross-validation with a set of images due to memory restrictions on Co-Lab. The experiment was performed with training-testing ratio as 80:20, for the experiment. There are various metrics to evaluate different deep learning methodologies' performance.The most common metrics, accuracy, precision, recall, and F1score, are used to evaluate the performance of the proposed method.

$$Accuracy = \frac{T^- + T^+}{T^- + T^+ + F^- + F^+}$$

True positives, false positives, true negatives, and false negatives may be designated by T^+,T^-, F^+, and F^-, respectively. In this case, the sensitivity of the classifier is calculated as the percentage of true positive that represent the proper identification during testing.

Measures of precision and recall are used to determine a classifier's accuracy and completeness.

$$Precision = \frac{T^+}{T^+ + F^+}$$

$$Recall = \frac{T^+}{T^+ + F^-}$$

Furthermore, to identify the optimal proportion of accuracy and recall, an F1-score measurement is required.

F1 score = $\frac{2*(\text{Precision.Recall})}{(\text{Precision+Recall})}$

Table 2.Comparison of experimental results using different well-known CNN architectures

Algorithms	Accuracy	Precision	Recall	F1 score
GoogleNet	83.87%	83.73%	84.04%	83.79%
VGG16	86.18%	86.74%	86.29%	85.54%
AlexNet	87.10%	87.64%	87.25%	86.81%
Proposed work	89.35%	88.85%	90.23%	89.64%

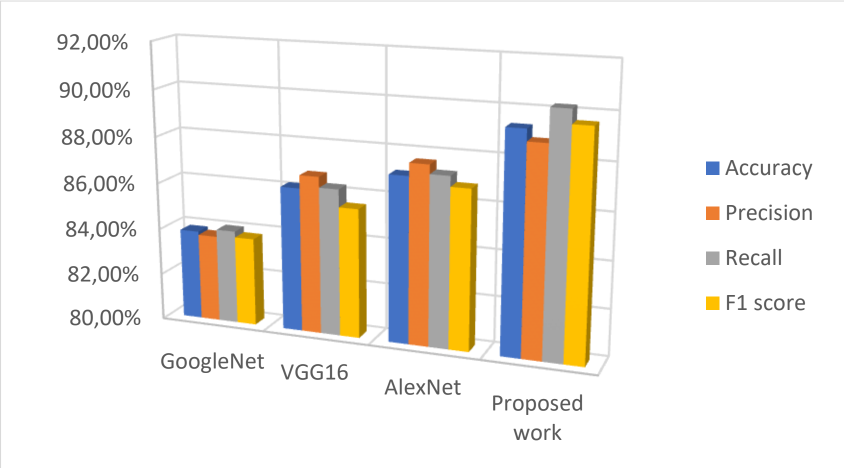

Figure 4. Comparison of experimental results using different well-known CNN architectures

From the figure 4, it is observed that the proposed work obtains the highest accuracy of 89.35%, GoogleNet obtains 83.87%, VGG16 obtains 86.18%, and AlexNet obtains 87.10%. The precision of the proposed work is 88.85%, GoogleNet, VGG16, and AlexNet obtains 83.73%, 86.74%, and 87.64% respectively. The recall obtained by GoogleNet, VGG16, AlexNet, and Proposed work is 84.04%, 86.29%, 87.25%, and 90.23% respectively. The F1 score of GoogleNet, VGG16, AlexNet, Proposed work is 83.79%, 85.54%, 86.81%, and 89.64% respectively.

Conclusion

Computer vision and AI frameworks are now generally utilized in various stages of producing agricultural and industrial foods. Because rice plant diseases can do a big amount of loss in the agriculture domain, these frameworks can be utilized for detection of various diseases of rice crop more efficiently. Utilizing these frameworks is efficient enough to computerize relentless assignments, in a non-dangerous way, creating enough information for future investigation. In this work, to detect the rice plant diseases, deep learning algorithms are proposed. The EfficientNet -U-Net is proposed to segment the images of the dataset and to classify the images CNN is proposed. The performance of the algorithms is evaluated in terms of accuracy, precision, recall and F1 score. The proposed work obtains the highest accuracy of 89.35%,

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