INTERNATIONAL JOURNAL OF PROGRESSIVE RESEARCH IN SCIENCE AND ENGINEERING, VOL.3, NO.12, DECEMBER 2022.

Rice Plant Leaf Disease Detection Using Deep Learning: A Review

P M Paithane [1], Mansi Mane[2], Sejal Shinde[2], Pranali Kulkarni[2], Dnyaneshwari Nalawade[2]

[1]Asst.Prof., Department of Computer Engineering, VPKBIET, Baramati, Pune, India.

[2] UG student, Department of Computer Engineering, VPKBIET, Baramati, Pune, India.

Corresponding Author:paithanepradip@gmail.com

Abstract: Image processing is becoming less important and has been replaced by deep learning for many tasks such as image classification and object detection. A deep learning model with multilevel structure. It is very useful for extracting complex information from input images. Deep learning uses neural network architecture to learn useful representations of features directly from data. However, so far, deep learning methods have rarely been applied to the task of detecting plant diseases, although some existing studies have focused on public datasets of enlarged images of plant leaves.

Key Words: — ***Deep Learning, GoogleNet, Resnet, Inception, VGG.***

I. Introduction

Plant disease outbreaks affect agricultural production. Food insecurity increases when plant diseases are not detected in a timely manner. Early detection is the basis for effective prevention and control of plant diseases and plays an important role in agricultural production management and decision-making. In recent years, the identification of plant diseases has become an important theme. Plants infected with this disease usually show distinct spots or lesions on leaves, stems, flowers or fruits. In general, each disease or pest condition has unique visual patterns that can be used to unambiguously diagnose anomalies. Plant leaves are usually the primary source of information for identifying plant diseases, and most disease symptoms appear on leaves. In most cases, agroforestry specialists identify them on site, or farmers identify fruit tree diseases and pests based on past experience.

Manuscript revised December 20, 2022; accepted December 21, 2022. Date of publication December 22, 2022.

This paper available online at www.ijprse.com

ISSN (Online): 2582-7898; SJIF: 5.59

This process is not only subjective, but also time consuming, labor intensive and inefficient. Inexperienced farmers may misjudge or apply drugs blindly during the identification process. Quality and performance also bring pollution and cause unnecessary economic losses. To address these issues, using image processing techniques to detect plant diseases has become a hot research topic.

- Lightweight Inception Networks for the Recognition and Detection of Rice Plant Diseases [1] Rice is considered to be a major food consumed in many regions, especially in Asian countries. Proven. In this work, the original convolution with DSC was replaced with an improved Inception module, and was paired with pre-trained MobileNet. It was chosen to extract high-quality image features of plant diseases. After that, a fully dedicated Softmax layer with practical category counts and SSD block were separately added behind the base network to implement image identification and recognition tasks. The traditional Inception module has been expanded to replace the standard fold with a depth-separable fold, reducing the number of model parameters while increasing model efficiency. We have combined MobileNet with the advanced Inception Module to form a new lightweight network, MobInc-Net. This network was chosen as the base network for extracting high-quality image features from plant diseases. For model training, a two-stage transfer learning (TL) was implemented with an optimized loss function. The proposed method achieves better performance than the conventional method and has some ability to detect diseases in rice. This model has relatively high accuracy and memory efficiency, but fine-tuning operations can further improve the performance of the model.

- Image processing-based rice plant leaves diseases in Thanjavur, Tamil Nadu [2] In this article, the authors (T. Gayatri Devi and P. Neelanegan) investigated the performance of different classifiers based on image processing techniques for automatically identifying leaf diseases in rice. The classifiers compared in this work are KNN (K nearest neighbors), neural networks, neural networks with backpropagation, naive Bayesian, and multiclass support vector machines (SVM). The models proposed in this paper are K-means clustering for image segmentation, median filter for denoising, discrete wavelet transform (DWT), scale-invariant feature transform (SIFT), and grayscale co-occurrence matrix (GLCM). Purpose of feature extraction. The extracted features are used by classifiers, these classifiers are trained and tested, and the multi-SVM classifier achieves a high accuracy of 98.63% for healthy leaves. There are various diseases on rice leaves. Of these diseases, we focus on five (smut, leaf blight, brown spot, leaf streak, and pseudo smut). For this research study, the dataset was provided by the Tamil Nadu Rice Research Institute (TRRI), Aduturai, Thanjavur. He further experimented with Matlab Tools.
- Rice Leaf Diseases Recognition using Convolutional Neural Networks [3] In this work, we use a novel convolutional neural network (CNN) model to identify diseases present in rice leaves. During the implementation of the CNN model, the network parameters are minimized and the Adam (adaptive moment) optimizer is used to reduce the loss and optimize the result by improving the learning rate of the model. The CNN model used consists of 10 layers. Input layer, 3 convolutional layers, 3 max pooling layers (each convolutional layer is followed by a max pooling layer), 2 dense layers with M sizes of 64 and 5 respectively, the last layer is softmax giving the output labels layer. The number of filters used in the convolutional layers are 16, 32, and 64. The activation function used in combination with each convolutional layer is ReLU (Rectified Linear Unit), which gives better results for rice leaf recognition using CNN than tanh's sigmoid activation function. The average accuracy of the proposed model is 97.82%.

The datasets used in this study were obtained from the International Rice Research Institute (IRRI) and the Bangladesh Rice Research Institute (BRRI). The model was trained with different rice leaf background images and different image sizes. Data augmentation with 12 different techniques (some degree of image rotation, image flip, etc.) increases the amount and quality of data in order to train the model better.

- The identification of corn leaf diseases based on transfer learning and data augmentation [4] In this work, the authors combined data augmentation and transfer learning using an improved convolutional neural network algorithm. The training dataset was enriched with his data propagation methods such as random clipping, horizontal flipping, vertical flipping and center clipping. After training, a model was built to rapidly identify maize leaf diseases. This model circumvents the problem that traditional neural network classification is prone to local optimization and overfitting for small datasets. He trained maize leaf images from the Plant Village dataset, which he grouped into four categories. The improved model accurately identifies maize leaf disease images. The detection rate was up to 97.6% for, which is a significant improvement in the detection speed of the model and consistent with its practical application of detecting leaf diseases in maize. Survey Table:

Table.1. Model-accuracy from reference research papers

Sr. No	Literature (Year)	Models/Algorithms	Accuracy
1.	[1](2022)	MobInc Model	99.43%
2.	[2](2018)	KNN	96.778%
		ANN	86.63%
		Naive Bayesian	85%
		Multi-SVM	98.63%
3.	[3](2021)	CNN	97.82%

4.	[4](2020)	CNN + (Data Augmentation + Transfer Learning)	97.6%

II. Disease Description

2.1 Materials

2.1.1 Disease Dataset

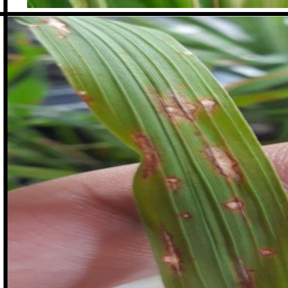
Common datasets used for experiments are from web crawlers, plant villages, and various research institutes (International Rice Research Institute (IRRI), Bangladesh Rice Research Institute (BRRI), Tamil Nadu Rice Research Institute). (TRRI), Aduturai, Thanjavur, etc.).

And the dataset we will be using for experiment is from Mendeley, an open source and secure cloud-based repository. The dataset contains images of four rice leaf diseases with 5932 total images (approximately 1500 images of each disease).

2.1.2 Disease Description

More than 10 different diseases are found on rice leaves. Among them are bacterial blight, blast, brown spot and tungro. Sample images of these diseases are shown in the figure below.

Table.2. Sample diseases (mendeley dataset)

Disease Name	Image Count	Sample Image
Bacterial Blight	1508	
Blast	1440	
Brownspot	1600	
Tungro	1308	

- Bacterial Blight: Bacterial Blight is caused by Xanthomonas oryzae. Symptoms of the disease include lesions that generally start at the tip of the leaf and spread several inches toward the base of the leaf. Blight is one of the devastating diseases that causes significant losses in rice production.
- Rice Blast (RB): RB disease is incited by Magnaporthe oryzae. Symptoms of the disease are spots with gray-green circles and a dark green border on the leaves. Lesions are oval or spindle-shaped. It is one of the most devastating rice diseases in various countries around the world (Kumar et al., 2016).
- Brown Spot: Infected seedlings have small circular tawny or brown lesions surrounding the coleoptile, which can distort primary and secondary leaves. During the initialization of the tillering stage, lesions are observed as small, round, dark purple or dark brown. Mature lesions are round to oval with a light brown to gray center. It is surrounded by a reddish-brown rim caused by toxins produced by the fungus.
- Tungro: Tunguro-affected plants show stunting and reduced tillering. The leaves are yellow or orange-yellow and may have rust-colored spots. Discoloration starts at the tip of the leaf and extends to the leaf blade or lower part of the leaf.

2.2 Algorithms

The goal of study is to find the best possible solution in deep learning to detect rice leaf diseases. The Deep Learning models we are analysing are VGG16, ResNet50, Inception, EfficientNetV2 for image classification. These models are based on convolution neural networks.

- VGG16: AlexNet is improved by sequentially replacing large kernel-sized filters (11 and 5 in the first and second convolutional layers, respectively) with multiple 3 × 3 kernel-sized filters. The input for the cov1 layer is a fixed size 224x224 RGB image (capturing left/right, top/bottom and center ideas). One configuration also uses a 1×1 convolution filter. This can be viewed as a linear transformation of the input channel (followed by the nonlinearity). The convolution step is fixed at 1 pixel. The layer input is such that the spatial resolution is preserved after convolution. That is, for H.3×3 transforms, the padding is 1 pixel. Spatial pooling is performed by up to five pooling layers followed by multiple transformations. Layers (not all transformation layers follow max pooling). In step 2, max pooling is performed on this 2x2 pixel window. Three fully connected (FC) layers follow the stack of convolutional layers (with different depths for different architectures).
- ResNet-50: To solve the Resnet50 gradient vanishing/exploding problem, the concept of residual block was introduced into this architecture. This network uses a technique called skip connections. Connection jumps between layers to connect activations in one layer to another. This forms the rest of the block. A resnet is built by stacking these remaining blocks. ResNet is an artificial neural network that introduces "identity connections" that allow the model to skip one or more layers. This approach allows the network to be trained with thousands of levels without sacrificing performance. This has made ResNet one of the most popular architectures for various computer vision tasks. In a detailed comparison of all current CNN architectures, ResNet has the lowest error rate of 3.57\% for the top 5\% of classification tasks, overtaking all other architectures. The human error rate is also not that low.
- Inception: Previous networks like VGG have achieved amazing accuracy on the ImageNet data set, but the deep architecture makes the deployment of these types of models very computationally intensive. There are a total of 22 layers in this architecture. The neural network architecture is built using the dimensionality-reduced initial modules. This is commonly known as GoogLeNet (Inception v1). GoogLeNet linearly incorporates 9 such starting modules. The depth is 22 layers (27 layers including the pooling layer). The global average pooling replaces fully connected layer and computes the average of each feature map at the end. This actually dramatically reduces the total number of parameters.This architecture captures 224 x 224 sized images with RGB color channels. ReLU is used as activation function for all convolution in architecture.
- EfficientNetV2: EfficientNetV2 is a type of convolution neural network and it is faster than previous versions of efficientNet and gives better results with fewer parameters. Scaling and neural architecture search forms the EfficientNet Model. The main aim is to optimize training speed and parameter efficiency. With more layers (depth) more complex features can be obtained, but these models are difficult to train due to vanishing gradients. By training with higher resolution images, the convnet can theoretically capture finer details. Again, the accuracy gain diminishes for quite high resolutions. EfficientNetV2 is 11x faster than previous EfficientNetV2-B0. The EfficientNet models reduce parameter size and FLOPS by an order of magnitude. They achieve higher accuracy and efficiency than CNNs.

III. MODELING AND ANALYSIS

A series of steps need to be carefully followed for the process need to be followed in a disciplined manner. Image Pre-processing and background removal: This is most important phase, as it involves the quality assurance of the data. In the image pre-processing phase image is processed to desired color format, resized to desired size and images are denoised. After that Image Segmentation is done to obtain the infected region. Region of interest that is the infected part of the leaf is identified. This is again one of the most crucial steps, as the entire analysis is dependent on the infected region identified by the process of segmentation. On the basis of the infected part of the leaf various image features like standard deviation, mean of red, blue and green channels, the entropy of image is extracted. The 70% of the split data is used for training the proposed model. In testing Data extraction randomly, the data in csv file is split. The 30% of the split data is used for testing the proposed model. The deep learning models such as Inception, ResNet50, VGG16, EfficientNetV2 are used for classification and evaluation metrics such as precision, recall, F1-score, and accuracy for each model will be obtained.

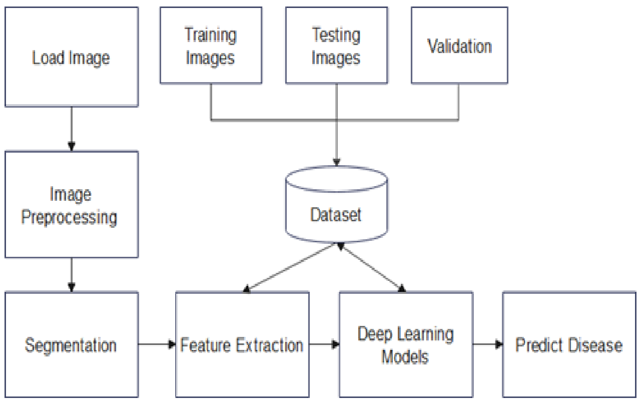


Fig.1. System Architecture

IV. CONCLUSION

Timely and effective detection of plant diseases is critical to avoiding the attacks of various plant diseases and ensuring food safety. Therefore, there is a need to look for simple, fast methods for automatic crop detection. A deep learning method, explicitly deep CNN, has shown great ability in addressing many technical challenges related to image recognition and classification. Identifying and detecting leaf diseases is a beneficial solution for farmers to prevent the decline in detection of plant diseases on large farms and increase rice crop production.To overcome these challenges, we compare ResNet50, EfficientNetV2, VGG16, Inception models and evaluate these deep learning models based on precision, recall, F1-score, training-validation accuracy metrics.

REFERENCES

[1]. Junde Chen, Weirong Chen, Adan Zeb, Shuangyuan Yang, and Defu Zhang." Lightweight Inception Networks for the Recognition and Detection of Rice Plant Diseases."

[2]. T. Gayathri Devi and P. Neelamegam "Image processing-based rice plant leaves diseases in Thanjavur, Tamilnadu," Cluster Comput., vol. 22, no. S6, pp. 13415–13428, Nov. 2019."

[3]. Syed Md. Minhaz Hossain, Md. Monjur Morhsed Tanjil, Mohammed Abser Bin Ali,Mohammad Zihadul Islam, Md. Saiful Islam , Sabrina Mobassirin, Iqbal H. Sarker,and S. M. Riazul Islam. " Rice Leaf Diseases Recognition using Convolutional Neural Networks."

[4]. Hu, R., Zhang, S., Wang, P., Xu, G., Wang, D., & Qian, Y. (2020). "The identification of corn leaf diseases based on transfer learning and data augmentation. Proceedings of the 2020 3rd International Conference on Computer Science and Software Engineering."

[5]. K. P. Ferentinos. "Deep learning models for plant disease detection and diagnosis," Comput. Electron. Agriculture., vol. 145, pp. 311–318, Feb. 2018.

[6]. Paithane, P. M., & Kakarwal, S. N. (2022). "Automatic Pancreas Segmentation using A Novel Modified Semantic Deep Learning Bottom-Up Approach. International Journal of Intelligent Systems and Applications in Engineering, 10(1), 98-104."

[7]. Paithane, P. M., & Kinariwal, S. A. (2015). "Automatic determination of clusters for NMKFC-means algorithms on image segmentation. IOSR J. Comput. Eng.(IOSR-JCE), 17, 12-19."

[8]. Paithane, P. M., & Kakarwal, S. N. (2018, December). "Automatic determination of cluster for multi kernel NMKFCM algorithm on image segmentation. In the International Conference on Intelligent Systems Design and Applications" (pp. 870-879). Springer, Cham.

[9]. Paithane, P. M., Kakarwal, S. N., & Kurmude, D. V. (2020). "Top-down method used for pancreas segmentation. Int. J. Innov. Exploring Eng. (IJITEE), 9(3), 1790-1793."

[10]. Paithane, P. M., Kakarwal, S. N., & Kurmude, D. V. (2020, December). "Automatic Seeded Region Growing with Level Set Technique Used for Segmentation of Pancreas. In the International Conference on Soft Computing and Pattern Recognition" (pp. 374-382). Springer, Cham.

[11]. Wagh, S. J., Paithane, P. M., & Patil, S. N. (2021, December). "Applications of Fuzzy Logic in Assessment of Groundwater Quality Index from Jafrabad Taluka of Marathwada Region of Maharashtra State: A GIS Based Approach. In the International Conference on Hybrid Intelligent Systems" (pp. 354-364). Springer, Cham."

[12]. Chanda, M., & Biswas, M. (2019). "Plant disease identification and classification using back-propagation neural networks with particle swarm optimization." Proceedings of the International Conference on Trends in Electronics and Informatics, ICOEI 2019, 2019-April (Icoei), 1029–1036.

[13]. Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D., and Stefanovic, D."Deep Neural Networks Based Recognition of Plant Diseases by Leaf Image Classification." Comput. Intell. Neurosci. 2016(2016).

[14]. Kiani, E., & Mamedov, T. (2017). "Identification of plant disease infection using soft-computing: Application to modern botany" Procedia Computer Science, 120, 893–900.

[15]. Jiang, F., Lu, Y., Chen, Y., Cai, D. and Li, G. (2020)." Image recognition of four rice leaf diseases based on deep learning and support vector machine" Computers and Electronics in Agriculture 179: 105824.

[16]. M. Tan and Q. V. Le, "EfficientNet: Rethinking model scaling for convolutional neural networks," 2019, arXiv:1905.11946.

[17]. G. Geetharamani and A. Pandian, "Identification of plant leaf diseases using a nine-layer deep convolutional neural network," Comput. Electr. Eng., vol. 76, pp. 323–338, Jun. 2019.

[18]. Kakarwal, S., & Paithane, P. (2022). "Automatic pancreas segmentation using ResNet-18 deep learning approach. System research and information technologies, (2), 104-116."