A Real Time Performance Comparison of Rice Plant Disease Identification System using Deep CNN Models

[1]K. Mahadevan, [2]Dr. A. Punitha, [3]Dr. J. Suresh, [4]Dr. P. Sivakumar,

[1]Research Scholar, Dept. of CSE, Annamalai University, Chidambaram, Tamilnadu – 608002
[2]Associate Professor, Dept. of CSE, Annamalai University, Chidambaram, Tamilnadu - 608002
[3]Associate Professor, Dept. of CSE, CARE College of Engineering, Trichy, Tamilnadu – 620009.
[4]Associate Professor, Dept. of CSE, Sasi Institute of Tech. & Engg., Tadepalligudem, Andhra Pradesh-534101

Submitted: 17 June 2022
Accepted: 31 Dec 2022
Published: 31 Dec 2022

Abstract

India is the second largest producer of the world and the largest exporter of rice. In order to ensure the healthy rice production, it is important to detect the diseases at early stage. Many approaches were proposed to solve the rice plant disease identification and it is identified through literature that those models were not given expected accuracy. In this study, an attempt has been made to determine the optimal suitable model among the four deep learning CNN algorithms to classify the rice leaf diseases. In this research study, 1600 images were used to classify into four class models: Healthy, brown spot, Hispa and leaf blast. From the results, performance comparison has been analyzed in terms of learning rate, precision and disease recognition accuracy. The deep learning CNN models, ResNet50, VGG19, InceptionV3, and ResNet152 have reached disease recognition accuracy of 75.76%, 87.64, 96.46% and 98.36%. The classification performance result demonstrates that Reset152V2 is the optimal CNN model can be used to classify of rice diseases.

Keyword: Leaf disease Detection, Image Classification, Rice Plant Leaf Disease identification

1. Introduction

The fundamental part of any ecosystem is plant. All living beings get energy from plants directly or indirectly. It is important to recognize the infection in plant parts like leaf, stem, and natural product. Leaf diseases are brought by infections, microbes, and so on. Regularly, a farmer distinguishes the leaf diseases by noticing spots, shading, and state of the leaf, however once in a while they take help from the specialists to recognize unhealthy leaf or harvests.

Rice is the most important human food crop in the world, directly feeding more people than any other crop. In 2012, nearly half of world‟s population – more than 3 billion people – relied on rice every day. It is also the staple food across Asia where around half of the world‟s poorest people live and is becoming increasingly important in Africa and Latin America. Rice has also fed more people over a longer time than has any other crop. It is spectacularly diverse, both in the way it is grown and how it is used by humans. Rice is unique because it can grow in wet environments that other crops cannot survive in. Such wet environments are abundant across Asia. The domestication of rice ranks as one of the most important developments in history and now thousands of rice varieties are cultivated on every continent except Antarctica.

Rice crop deals with numerous issues because of infections which influence it a lot and it is difficult to recognize it by naked eyes. The generally influenced part for the infection is leaf of the plant. Around 80 to 90%

of diseases on the plant is on its leaves. So, in this paper we concentrate mainly on the leaf part rather than the entire plant. Many methods were proposed to identify the diseases in rice plants using it‟s Leafs. Many of the methods were failed to give more identification accuracy.

The main objective of this work is to decrease the losses caused by plant diseases in farming. So, in this paper we proposed to use four CNN architectures like ResNet, Resnet152V2, VGG19 and InceptionV3, used to identify the diseases in rice leafs. In this proposal we provided an idea of using a transfer learning technique to all the four models to identify the disease on leaves. The remaining section of the paper consists of related work, proposed method methodologies and results.

The rest of this paper was organized in such way that the paper contains the sections such as related work, methodology, proposed work and results and discussion.

2. Related work

Anand et al. [4] introduced a technique for the location of leaf infections in the brinjal plants utilizing RGB pictures. About 85% of the diseases in brinjal plants happen in the leaves making it the space of interest for disease recognition. Thermal pictures catch the infrared radiations produced by the leaves and the power of every pixel depicts the temperature at that actual point. Hence thermal images have a fine potential for early recognition of infections because of the temperature varieties that are noticed.

Veni et al. [6] proposed a model which can detect healthy and unhealthy leaves. In order to classify healthy and unhealthy leaves, they used image processing techniques. For this experiment, brinjal datasets are used. RGB and Thermal cameras are used to collect brinjal leaf datasets. By considering color and temperatures as the main feature they got an accuracy of 90.9% with SVM and an accuracy of 89.1% with ANN.

Galip and Fatih [7], done various implementations for comparing different types of activation functions. Some of them are tanH, sigmoid, ReLu, soft plus on classification. Among all these ReLu got the highest accuracy i.e., 98.43%. From the results, they came to know that if the number of iterations increases, the accuracy also increases.

Robert G. de Luna et al. [12] proposed an automatic system that captures images automatically. They proposed this system for identifying the diseases in tomato leaves. They used a transfer learning model for achieving this. By implementing this they got an accuracy of 95.75%. But the previous works did for identifying diseases in tomato leaves got only 91.67% accuracy.

Melike Sardogan *et al.*[15], proposed a CNN model for extracting features automatically and also for classifying the diseases found in plants. For achieving their idea, they have utilized Learning Vector Quantization (LVQ). For implementing this, they collected the dataset which contains 500 images of diseased tomato leaves. To increase the accuracy they used Supervised learning neural networks algorithm. For classifying different diseases in tomato leaves, LeNet is slightly modified and used.

Peng Jiang *et.al.* [17] in their paper used a deep convolutional neural network for identifying diseases in apple plant leaf. This is a real-time model. For the training model, Google Net is used. This model is capable of extracting features automatically. It identifies different types of 5 diseases in plants.

Santhana Hari [18], introduced a new CNN model which helps in extracting features from the images of leaves of different yields. The new CNN model introduced is Plant Disease Detection Neural Network. This model has 16 layers and 32*32 filters. They implemented this model on the dataset of 14810 images. By using this model, they achieved a higher accuracy i.e., 86%. When compared with MobileNet50 they observed that the accuracy has increased 7%.

It is observed that the models discussed in the literature survey are not used any Keras models for rice leaf disease detection. It is also identified that the existing models are not given expected accuracy and performance up to the expected level.

So it is proposed to use various Keras models for rice leaf disease identification in early stage to help formers for early prediction of fertilizers and drugs to recover from the heavy loss due to leaf diseases.

It is also aimed to check the performance comparison of those models and to check whether which model is performing well for the selected dataset.

3. Proposed work

After studying the various approaches and methods towards disease detection in leaves a new idea that will improve the accuracy of diseases detection has been used. Fig 1 shows the architecture of rice leaf disease detection model.

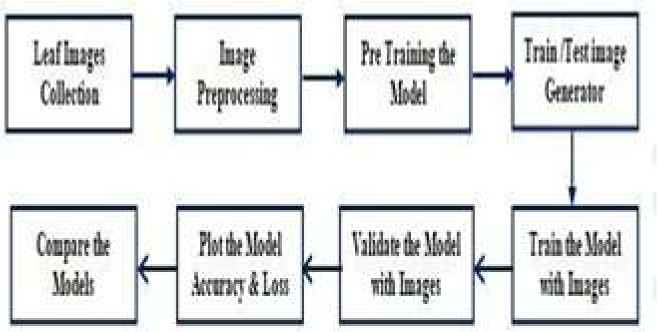

Fig.1. Block diagram of the proposed method

Fig. 1 explains detailed information about rice leaf disease detection. The user uploads the images of the leaves and clicks the predict button to get the output. When the user clicks the predict button it calls the API. The API takes the file and converts the image into array. In the next step the array is normalized. Later depending upon the normalized value, it predicts whether the image is diseased leaf image or fresh leaf image.

4. Methodology

ResNet50

CNN is heavily used for image processing related applications because of higher accuracy with reduced error rates when compared to predecessors. It is also used to detect the features from the images given as input. It consists of convolutional layers with ReLu function and pooling layers to reduce the size of input features from the convolutional matrix. Another significant advantage of CNN is that it will do both fact use extraction as well as classification tasks.

The major challenge is CNN architectures in deep learning are too compact vanishing exploding gradient problems to reduce error rates increasing the accuracy of the model due to overfitting.

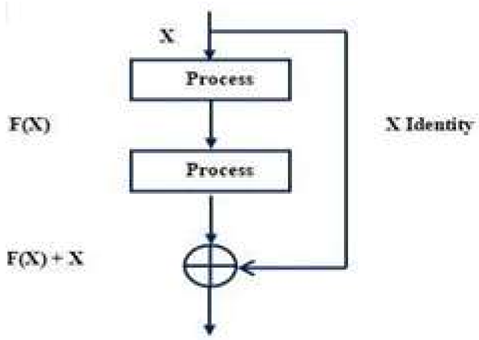

Fig.2: A Residual Block

ResNet which was residual networks architectures introduced at Microsoft in 2015 to combat the above challenges it also consists of skip connections which skips some layers while training the models. Let us assume H(x) will be initial mapping then f(x)= H(x)-x which gives H(x) = f(x) +x.

The addition of this layer will increase the accuracy by skipping the poor performing layers this reduced the problems of exploding gradient in this paper ResNet50 is another version of ResNet used for rice plant disease identification system. The figure 3 gives the details of the ResNet50 architecture.

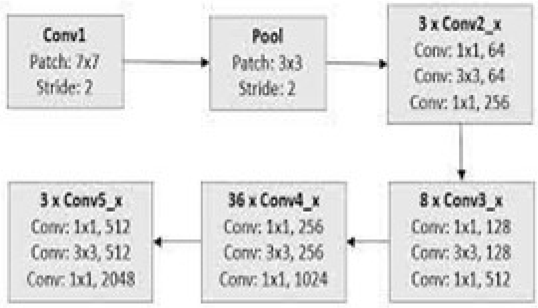

Fig3: ResNet50 Layers Structure

VGG19

VGG19 is a type of deep convolutional neural network used for image classifiers and it is a variant of VGG model. This model consist of totally layers in which 16 convolution layers, 3 fully connected layers ,5 max pool layers and 1 softmax layers. VGG was developed by visual Geometry group [VGG] at oxford, It is a successor of the AlexNet. VGG19 is a pre-trained CNN the number stands for 19 layers including 16 convolutional layers three fully connected layers. VGG19 is also one of the traditional conventional neural networks as a successor of AlexNet and it was proposed at oxford university VGG19 is a pre-trained model which was trained using the image net having more than 14,197,122 images.

Table I: VGG19 LAYERS

Layer Name	#Filters	# Parameters	# Activations
Input			150K
C1_1,C1_2	64	17K,36K	3.2M
Max Pooling			802K
C2_1,C2_2	128	73K,147K	1.6M
Max Pooling			401K
C3_1, C3_2, C3_3, C3_4	256	300K, 3 x 600K	802K
Max Pooling			200K
C4_1, C4_2, C4_3, C4_4	512	1.1M, 3x 2.3M	401K
Max Pooling			100K
C5_1, C5_2, C5_3, C5_4	512	2.3M	100K
Max Pooling			25K
FC6		103M	4K
FC7		17M	4K
Output		4M	1K

It is also used for both image classification and feature extractions.The input color image size of 224×224 is given to VGG19 architectures. It is identified that VGG19 is the best classifier for various image datasets. This is also the best model for transfer learning through pre-trained images it is one of the computationally efficient architectures. The total number of layers available in each stage is given in Table I. It is also applied the kernels of 8120 3×3 with a stride size of 10. It involves spatial padding techniques to protect the spatial features of the image. This model also uses RELU to improve the nonlinearity of image features to help increasing classification accuracy and training time. VGG19 is used here for both feature extraction and classification of the rice leaf disease identification system.

InceptionV3

InceptionV3 is one of the Deep Convolutional architectures from Google. Google introduced the inception deep convolutional neural network and named as GoogleNet [1] in 2015 also called as InceptonV1. Then batch normalization technique was introduced and the new version was named as IniceptionV2. Later factorization idea was added and the new version is called as InceptionV3.

InceptionV3 is also a pretrained model, it was pretrained using ImageNet dataset which contain 1000 classes of more than 12 million high resolution images among 100000 training images and 50000 testing images. InceptionV3 uses the knowledge gained from the ImageNet dataset and applies this knowledge to new dataset for any application and this concept is called transfer learning. Transfer learning is nothing but learning through over millions of images in powerful machines. This model uses this knowledge learned through this training, apply to other small sized dataset. Thus this model will yield higher classification accuracy using this transfer learning. This pretrained InceptionV3 can capable of classifying images of 1000 classes. It contains 48 layers. Inception V3 is a kind of convolutional neural network contained 48 deep layers. Inception V3 in pre-trained with ImageNet dataset which contains more than one million images. It is the necessary inception V1 and inception V2. Inception v1 model contains 5×5 convolution which leads to a decrease in the Dimensions by large numbers which leads to a decrease in inaccuracy. InceptionV2 compact the problems by reducing the size of convolution from 5x5 to 3x3. This leads to an increase in the accuracy at the same time decreases the computational time. Thus, the performance of the InceptionV2 is increased due to the convolutional size change. InceptionV3 is similar to InceptionV2 but it uses an RHSprop optimizer. It also has Batch Normalisation in the fully connected layer

InceptionV3 get input images of 8,120 (299,299,3) it is proved that Inception V3 is giving the highest accuracy when compared to its predecessor in both classic fictions on well on feature extraction it has Label Smoothing technique to regularize components which are added to the loss formula. Total number of layers available in InceptionV3 model is given in the Table II.

Table 2: INCEPTIONV3 LAYERS

CNN LAYER	FILTER SIZE	NO OF KERNAL	STRIDE
C1	3X3	3	2
C2	3X3	32	1
C3	3X3	32	1
P1	3X3	64	2
C4	3X3	64	1
C5	3X3	80	2
C6		192	1
3 1M		288	
5 1M		768	
2 1M		1280	
P	8X8	2048	0
LINER	1X1	2048	

This InceptionV3 is applied to detect the disease in rice plants it is preferred to use here because of the higher accuracy with reduced error rates and also the reduced computational time.

ResNet152V2

Similar to the above model, in ResNet 152 v2 the post fix „152" represents the number of layers in the model.

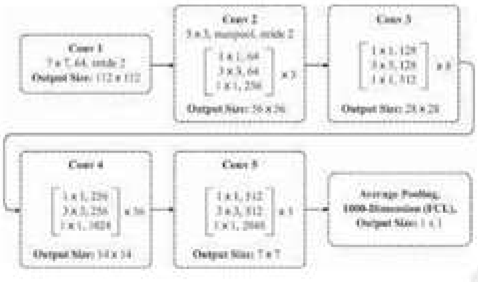

Fig4: ResNet152V2 Layers Structure

The 152-layer ResNets are constructed using more 3-layer blocks. Even after the depth is expanded, the 152-layer ResNet has lower intricacy than VGG16.

5. Experimental Setup

Top performing keras models such as InceptionV3, ResNet152v2, ResNet50, and VGG19 were used for checking the performance in identifying the rice leaf diseases. The model performance was checked by implementing this using Jupyter Notebook under Anaconda IDE by using Python 3.8 as a coding language. The frontend tools used for implementing the project are Visual Studio Code and Jupyter Notebook. This work also used a backend frame work called FLASK.

Experiments were conducted with by applying each model with dataset separately and the accuracy and loss obtained during this experiment is compared.

Transfer Learning

The four models used here for the identification of rice leaf diseases were pretrained by using ImageNet dataset which is large repository of images of more than 1 million. Our model transfers knowledge learns from the ImageNet and applies this knowledge over the rice leaf dataset. This transfer learning is identified to increase the identification accuracy. All the four models used here were pretrained.

Data Collection

In this research study, rice leaf database has been used from the Kaggle website. Deep learning model requires a large amount of images in order to give better classification results. The rice leaf database consists of total of 2092 images out of which 1600 images for training the deep learning model and 492 images for validation and testing. Among these rice leaf database, 400 images were for brown spot diseases, 400 images were for leaf blast diseases and 400 images were for Hispa diseases. These images were captured using high resolution cameras with an image pixel around 2 Megapixel. In order to prepare the deep learning CNN model, the images were split into training set, a validation set and a test set with a ratio of 7:2:1.

Four different CNN architectures were developed and dataset were applied to three diseases categories.

Data set

The dataset used for the implementation of the above models consists of two sets, testing set and training set. The test set and training set consists of 4 folders. The dataset is downloaded from Kaggle website [22]. Table III contains details about folders and the number of images available in training and validation folder.

ISSN: 2326-9865

Table 3: DATASET DESCRIPTION

Training set	Qty	Validation Set	Qty
Brown Spot infected	400	Brown Spot infected	123
Healthy Leafs	400	Healthy Leafs	123
Hispa Infected	400	Hispa Infected	123
Leaf Blast Infected	400	Leaf Blast Infected	123

6. Results

After experiments were conducted, it is observed from the results that ResNet152V2 achieves an accuracy of 98.36%, InceptionV3 achieves an accuracy of 96.46%, VGG19 achieves an accuracy of 87.64% and ResNet50 achieves an accuracy of 75.76%. The output after execution will be as shown in the following figures.

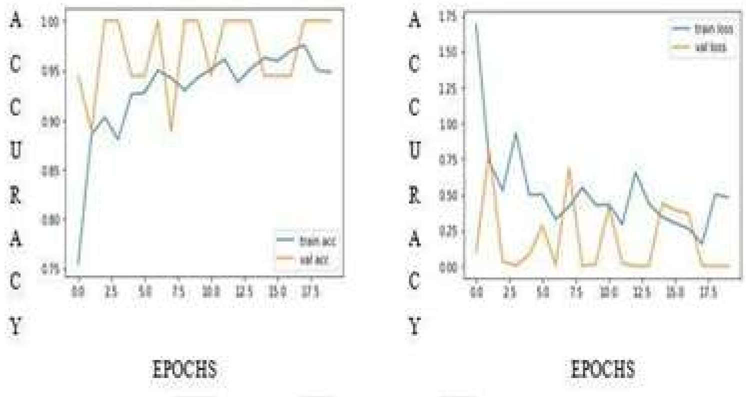

Fig.5. a) Accuracy Graph of Inception V3 b) Loss Graph of Inception V3

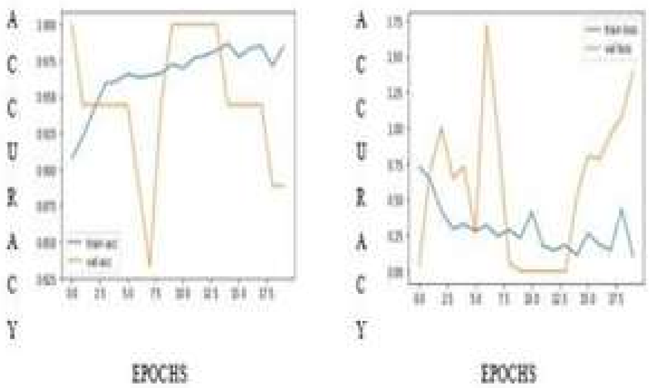

Fig.6. a) Accuracy Graph of ResNet 152V2 b) Loss Graph of ResNet 152V2

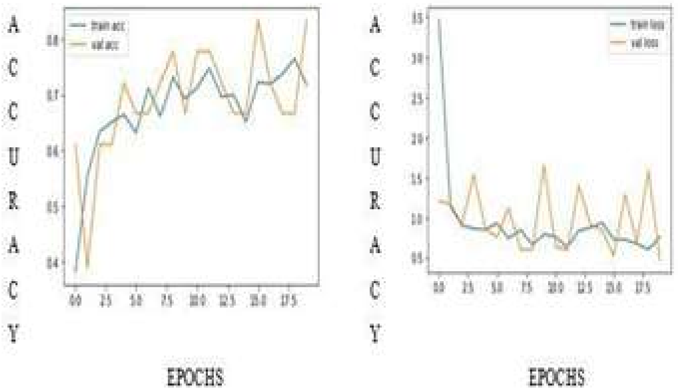

Fig.7. a) Accuracy Graph of ResNet 50 b) Loss Graph of ResNet 50

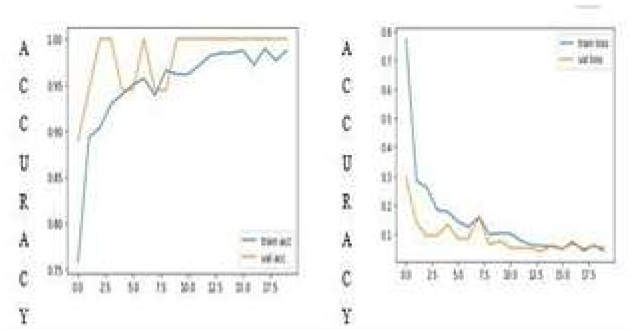

Fig.8. a) Accuracy Graph of VGG 19 b) Loss Graph of VGG 19

As expected, the ResNet152V2 model shows the highest accuracy compared to the remaining three models. Table III contains the details of performance comparison of various Keras models after implementation using the dataset.

It is observed that ResNet152 model having 152 layers outperforming than other three models. It is also identified that if the number of layers are more, the accuracy of the classification also increased. ResNet152V2 have more training from the input dataset due to more layers and given more accuracy.

Table 3: COMPARISON OF CNN MODELS

Model	No. of layers	No. of Parameters	Accuracy
ResNet50	50	2,56,36,712	75.76%
VGG19	47	14,36,67,240	87.64%
InceptionV3	48	2,38,51,784	96.46%
ResNet152V2	152	6,03,80,648	98.36%

The following bar chart represents the accuracies of ResNet50, VGG19, InceptionV3, ResNet152V2.

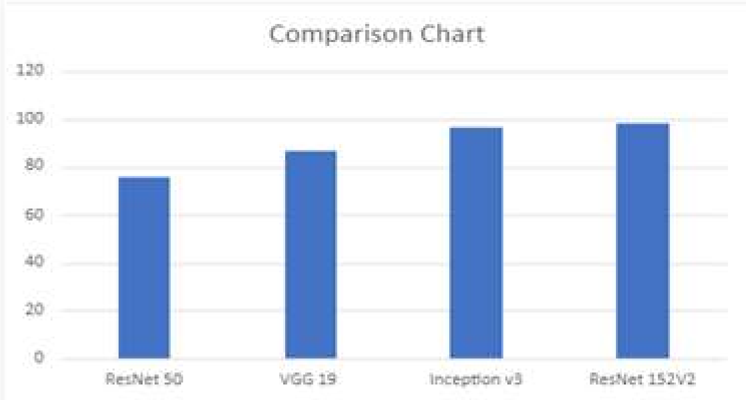

Fig.9. Comparisons of CNN Models

7. Discussion

CNN architecture configuration has been shown in the Table 2. The CNN architecture consists of filter size, No. of Kernels and stride. From the Table 2, it was observed that filter size of 3x3 has been used in the convoluted layers from c1 to c5. In this experiment, 400 leaf blast and 400 hispa images were given to the CNN architecture. No. of kernels linearly increases as level of the layers increases. The maximum kernel used was 2048. Different CNN models were employed to evaluate the performance of the rice leaf diseases is shown in the Table III. In this research study, 400 Leaf Blast and 400 Hispa images were given to four different CNN models such as ResNet50, VGG19, InceptionV3 and ResNet 152V2. From the Table III, it was observed that ResNet50 model used 50 layers and reached a classification accuracy of 75.76 per cent. Further, it was observed that VGG19 model used 47 layers and gave a classification accuracy of 87.74 percent. InceptionV3 model used 48 layers and achieved a classification accuracy of 96.46 per cent. Finally, experiment study used ResNet152V2 with 152 layers and gave accuracy of 98.36 per cent. From the results, it can also be noted that ResNet50 gave minimum classification accuracy and ResNet 152V2 achieved maximum classification in classifying the rice leaf diseases. From the research study, it can be concluded that Reset152V2 is the optimal CNN model can be used to classify of rice leaf diseases.

8. Conclusion and future enhancement

This research concentrates on rice crop leaf disease detection method. The fundamental cause of infection on rice plant is leaf of plant. Human eye can"t be able to differentiate variation in colour and texture change on rice leaf. So, an alternate is required for detecting diseases on plants. In order to deploy automatic classification of rice leaf detection, different deep learning algorithm has been used to determine the suitable classifier. In this work, we classified the diseases in rice leaf using transfer learning models. When compared with the existing methods in the literature those used four different Keras models for implementing this method. The four models ResNet50, VGG 19, InceptionV3, and ResNet152V2 are applied on the same data sets and their accuracies are 75.76%, 87.64%, 96.46%, 98.36% respectively. Among the four models ResNet152V2 with parameters 60,380,648 gave more accuracy. It can be concluded that Reset152V2 is the optimal CNN model can be used to classify of rice leaf diseases. For the future enhancement of this idea, the model suggested in this work can be implemented on different plants for disease identification. In this work, we focused only on the rice plant. But the disease detection approach is necessary for every crop. So, this paper can be further enhanced for classifying diseases in various plants which will be very helpful for agriculture sector

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