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Crop Guru: Deep Learning for precise and rapid plant disease diagnosis

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Abstract:

Sugarcane is cash crop in India and is also popular crop in Western Maharashtra, with millions of hectares of land dedicated to its cultivation. However, sugarcane crops are vulnerable to several diseases that can cause significant yield loss. In this research, we present an original and innovative approach for sugarcane crop disease detection by utilizing a Convolutional Neural Network (CNN). The proposed approach involves training a CNN model to automatically learn the features of sugarcane leaf images and classify them into healthy or diseased categories.To assess the efficiency of our proposed approach, we employed an openly accessible dataset containing sugarcane leaf images encompassing three distinct disease categories.The dataset was pre-processed and augmented to increase its diversity and size. CropGuru model trained and evaluated using an augmented dataset, demonstrating an impressive overall accuracy of 95.2% on the test set.Moreover, we conducted a comparative analysis, pitting our proposed CNN model against other state-of-the-art classification techniques. The findings conclusively revealed that the CNN model outperformed all other methods, showcasing its superiority in sugarcane crop disease detection.The proposed CNN-based sugarcane crop disease detection system can be a valuable tool for farmers and researchers to quickly and accurately identify the disease-affected crops in turn, they are able to act effectively to stop the spread of disorders and reduce crop production loss.

Keyword: Deep Learning, Convolution Neural Network, Plant disease detection

Introduction:

Sugarcane is one of India's most important crops, contributing significantly to the world economy. However, sugarcane crops are susceptible to a number of illnesses that can result in severe output loss, threatening farmers' and the sugar industry's lives. Early diagnosis of sugarcane crop diseases is critical for mitigating their harm. Detecting sugarcane crop diseases has traditionally been done through manual inspection, which is time-consuming, subjective, and error-prone. As a result, the development of an automated and precise approach for detecting sugarcane crop disease is critical.

Deep learning-based algorithms have yielded encouraging results in a variety of computer vision applications, including picture classification, in recent years. CNNs are a sort of deep neural network that have been frequently employed for image categorization applications. CNNs have demonstrated exceptional accuracy in recognising and categorising objects in images, making them a promising tool for automated disease detection in sugarcane crops.In this study, we suggest a CNN-based technique for detecting sugarcane crop disease. The suggested method comprises training a CNN model using photos of sugarcane leaves with various disease classifications. The trained model can then be used to categorise photos of sugarcane leaves as healthy or unhealthy. The proposed method can greatly reduce the time and effort necessary for sugarcane crop disease identification, allowing farmers to take proactive measures to prevent disease spread and crop yield loss.

The rest of the paper is organized as follows: Section 2 provides a review of related work in the field of sugarcane crop disease detection. Section 3 describes the dataset used for training and testing the proposed CNN model. Section 4 details the proposed CNN model architecture and the training process. Section 5 presents the experimental results and compares the performance of the proposed approach with other state-of-the-art techniques. Finally, Section 6 concludes the paper and discusses future directions for research.

Literature Review:

Mohit Agarwal uses a transfer learning method for Tomato plant disease detection. Mohit extensive research on 9 different diseases of tomato crop for disease classification[1].Mohit use plantvillage dataset for experimentation of tomato plant disease detection. Rangarajan and colleagues conducted training experiments on both AlexNet and VGG16net models, utilizing a minimum batch size of eight and bias learning rate as hyper-parameters[2]. The research findings revealed a negative correlation between the accuracy and the minimum batch size, particularly in the case of the VGG16net model[3].PBedi uses a peach plant for experiment .Bedi uses a convolution auto-encoder and CNN for automatic plant disease diagnosis. This hybrid model has very good accuracy nearly 99% in experiment with peach plant. I. Ahemadetl. collect the images from different tomato fields and used for disease classification using CNN model like VGG-16, VGG-19,Inception V3,DenseNet [5].Ahemad model show very low accuracy in real world. M Chowdhury [6],kibiriya[8] work for tomato plant disease detection as it is popular crop from India. A.Islam [7] employ deep learning technology model for early disease diagnosis for paddy crop in Bangladesh. M chohan in 2020 using a PlantVillage dataset done the plant disease detection for 5 different category of plant like Corn, Strawberry, Tomato, Apple. Table 1 provide an extensive literature review for Plant disease detection.

Table 1: Background Study for Plant disease detection

Sr. No	Reference	Plant For experiment	Dataset	Advantages	Limitation of work
1	Agarwal M(2020)	Tomato	Plant village	9 different disease are consider for work	Achive very less accuracy
2	Rangarajan (2018)	Tomato	Plant village	Uses AlexNet and VGG-16 model for experiment	Uses minimum batch size for training
3	Bedi P.(2021)	peach plants	Plant Village	High accuracy obtain in training & testing.	Bacterial Spot disease is detected by this model on peach plant
4	S. Ashok (2020)	Tomato	Plant Village	For detection of disease used algorithm that is open-source algorithm and image segmentation clustering	Work only 4 disease category of tomato plant
5	I Ahmad (2020)	Tomato	Author dataset	Experiment on VGG-16,VGG-19,Inception V3,Densenet.	Model do not show good accuracy for field collection data.
6	Muhammad E. H. Chowdhury (2021)	Tomato	PlantVillage	U-net image segmentation are used. Author developed	Author not validate the performance in real world

				different model for binary classification and multiclass classification	
7	Md.A. Islam (2021)	Paddy	Author dataset	Experiment on VGG-16,VGG-19,Inception-Reset V2,Resnet101	Author not validate the performance in real world dataset. Training dataset images are less
8	HKibriya (2021)	Tomato	PlantVillage	Uses VGG-16,Googlenet model for Tomato plant disease detection. Able to achieve good accuracy.	Author not apply model in real world images.
9	M Chohan (2020)	Tomato, corn, Staberry	PlantVillage	Consider 5 different category of plants for disease detection	Testing accuracy is less
10	J.Bhosale(2023)	Rice	Author own dataset	TF models VGG-16, ResNet50, and InceptionV3 results compared in identification of rice leaf diseases	Model fail to identify different rice varieties.
11	Andrew J(2022)	Several Plants	PlantVillage	Experimentation done with 38 different varieties of plant	Disease can't detect from bunch of Leaves
12	lili li1(2021)	cotton	Author own dataset	Deep learning model used for recognition.	Symptoms not clearly mention.
13	Sridevi	Paddy	Authorized dataset	unique DCNN-CS classification algorithm is used to identify leaf illnesses in paddy datasets.	Achieve good accuracy than embedded computer vision.
14	G. k. v. l. udayananda	Rice	PlantVillage	Hybrid model help for plant disease diagnosis ·	diseases detection is done by regular mapping approach in rice plant
15	N. Hussain	cucumber	PlantVillage	Efficiently identify cucumber disease. Able to achieve higher accuracy for single cucumber.	Low performance in recognition of multiple cucumber diseases
16	Muhammad R.L. ()	cotton	Author dataset	Cubic SVM is used to model development. Genetic algorithm is used to choose the top spots for additional recognition	Small number of training images
17	J. Arun Pandian	Citrus Banana tea	Plant Village	Model uses GAN and Random search technique for better results.	Estimation is pending for probability of plant
18	Murk Chohan	37 plants	Plant Village Dataset	Model explore the feature extraction feature of CNN for 37 different plants.	Accuracy is less for real time images
19	Konstantinos P.	several	Authorized dataset	Able to achieve high accuracy	Model shows less accuracy in real word scenes recognition.

20	Srdjan Sladojevic	several	Authorized dataset	Model help to identify 13 different categories of disease for several plants and also recognises healthy plant	Less train data. Real time implementation have low accuracy

There is a lack of research on using CNNs for detecting sugarcane crop diseases, with most existing research using traditional machine learning techniques. Additionally, previous studies have focused on a limited number of disease categories. This paper proposes a CNN-based approach for detecting multiple sugarcane crop diseases simultaneously, with the aim of developing an accurate and efficient method that can benefit farmers and the sugar industry.

Objective of Proposed work:

1) To suggest a CNN-based strategy for the automatic diagnosis of illnesses affecting sugarcane crops.

2) To develop a dataset of sugarcane leaf images with multiple disease categories for training and testing the proposed CNN model.

3) To evaluate the performance of the proposed CNN-based approach against other state-of-the-art techniques for sugarcane crop disease detection.

4) To demonstrate the potential of the proposed approach for accurate, efficient, and reliable detection of multiple sugarcane crop diseases, which can benefit farmers and the sugar industry.

Methodology:

Crop Guru has been developed in several stages, including data collection, pre-processing, dataset generation, data augmentation, transfer learning model -VGG-16, model training, performance evaluation on validation data, and model optimisation using random search.

Figure 1 shows detail diagrammatic description of Crop Guru .

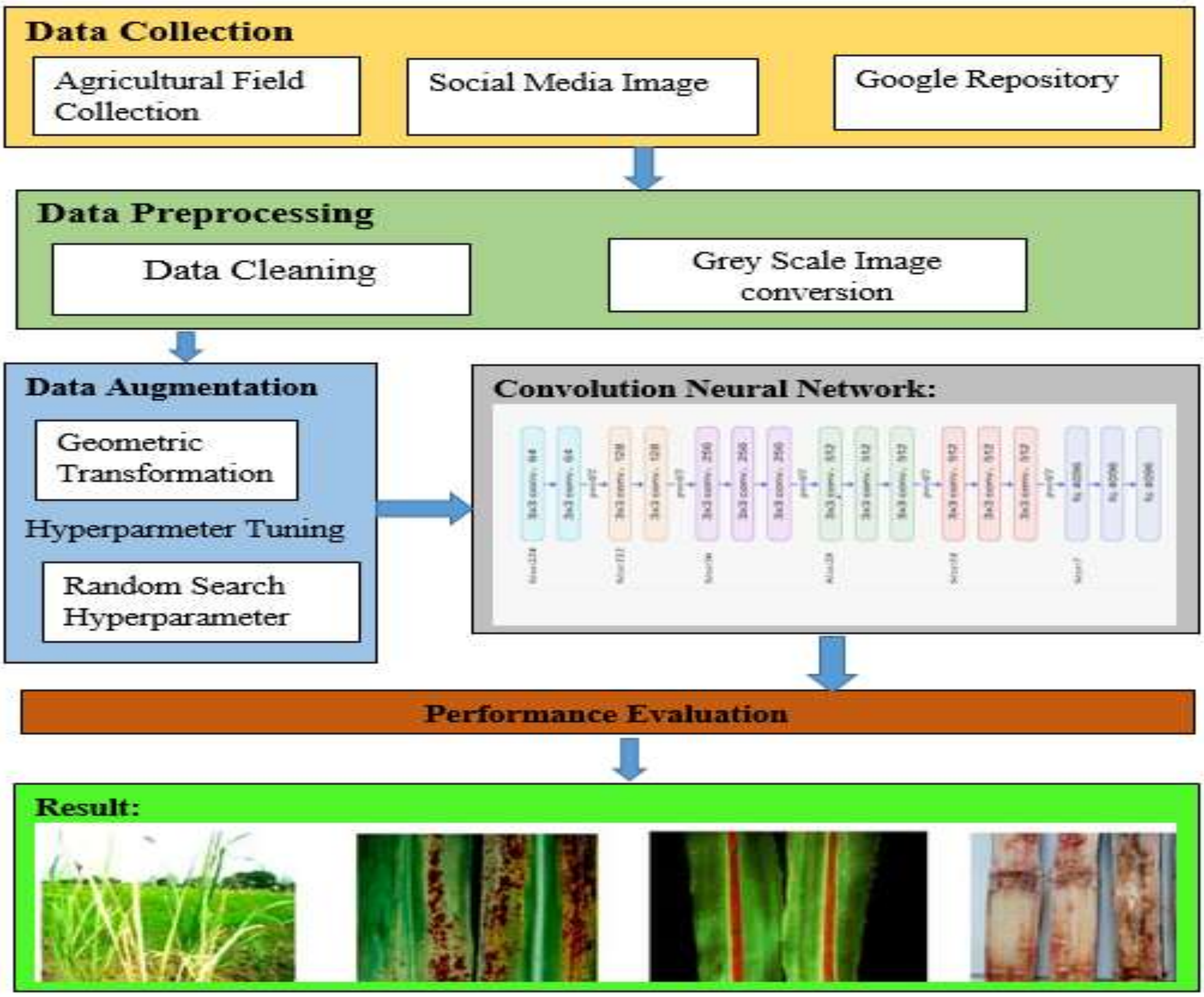

Figure 1: System Architecture for CropGuru

Data Collection: Sugarcane leaf pictures were obtained for this study from a variety of sources, including field surveys, research publications, and online repositories. The photos were filtered and labelled according to their disease categories, which included healthy leaves as well as leaves damaged by typical sugarcane diseases like red rot, yellow spot, and rust. We recruited experienced plant pathologists to check the labelled photos to confirm the dataset's validity.

Data Pre-processing: The data pre-processing process involved resizing, cropping, and normalizing the sugarcane leaf images to prepare them for training the CNN model. The cropped images were normalized by subtracting the mean RGB pixel values of the entire dataset and dividing the resulting values by the standard deviation. This step helped in reducing the variation in pixel values across the images and making the dataset suitable for training the CNN model.

Dataset Formation: The pre-processed images slash into training, validation, and testing sets in a stratified manner, ensuring that the distribution of the different disease categories was balanced across the sets.

Data Augmentation: To increase the diversity of the sugarcane leaf image dataset and improve the generalization ability of the CNN model, data augmentation techniques were applied. The data augmentation process involved randomly applying transformations to the input images during training, such as rotation, translation, flipping, and shearing. Additionally, random noise was added to the images to simulate the effects of real-world imaging conditions. The augmented images were then used in the training process, increasing the effective size of the dataset and allowing the CNN model to learn more robust features. The use of data augmentation helped in improving the model's performance by reducing overfitting and increasing its ability to generalize to unseen sugarcane leaf images.

Hyperparameters Tuning:

Deep neural networks involve a significant number of parameters or weights that are learned during the training process. Additionally, neural networks require specific hyperparameters that must be configured by the user. Examples of such hyperparameters include the learning rate and batch size, which are crucial for achieving good coverage of local optima, dropout to prevent overfitting of the training data, and determining the number of layers and filters per layer to define the model's capacity and inductive bias. Setting these hyperparameters often involves a time-consuming and challenging trial-and-error process. Furthermore, hyperparameters are typically not directly transferable across different neural network architectures and datasets, necessitating re-optimization for each new task. Unfortunately, there are no rule-of-thumb guidelines for most hyperparameters, making it essential to possess expert knowledge to select sensible values.

To address these challenges in deep learning architecture, researchers utilize Hyperparameter Optimization (HPO) techniques. Traditional HPO methods include Random Search, Grid Search, and Bayesian optimization. These approaches aim to automate the process of finding optimal hyperparameters, alleviating the burden of manual tuning and improving the performance of deep learning models on various tasks.

Grid search: the user enters a finite number of values for each hyperparameter, and grid search computes the Cartesian product of these values. Grid search is suitable for small size dataset as dataset increases number of evaluation functions grow exponentially which lead to time consuming and expensive.

Random Search: As name suggested it searches a domain space and select sample points randomly. This works better than grid search when some hyperparameters are much more important than others. Random Search can be easier parallelization, flexible resource allocation. Grid Search:

Bayesian optimization: Bayesian optimisation uses a probabilistic models strategy that approximates the relationship between hyperparameters and an objective function and then uses an acquisition function to decide best hyperparameters combination.

Final Hyperparameters after values after Hyperparameters optimization shown in Figure 2.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 24, 24, 128)       3328

 conv2d_1 (Conv2D)           (None, 20, 20, 64)        204864

 flatten (Flatten)           (None, 25600)             0

 dense (Dense)               (None, 96)                2457696

 dense_1 (Dense)             (None, 10)                970

=================================================================
Total params: 2,666,858
Trainable params: 2,666,858
Non-trainable params: 0
_________________________________________________________________
```

Figure 2: Final model hyperparameters values

Convolution Neural Network (CNN):

CNN stack of layers used for feature extraction from images. CNN layer stack mainly consists of convolution layer, Relu, Pooling layer, dense layer with soft max activation function. Figure 4 represent the CNN model architecture used in Crop Guru.

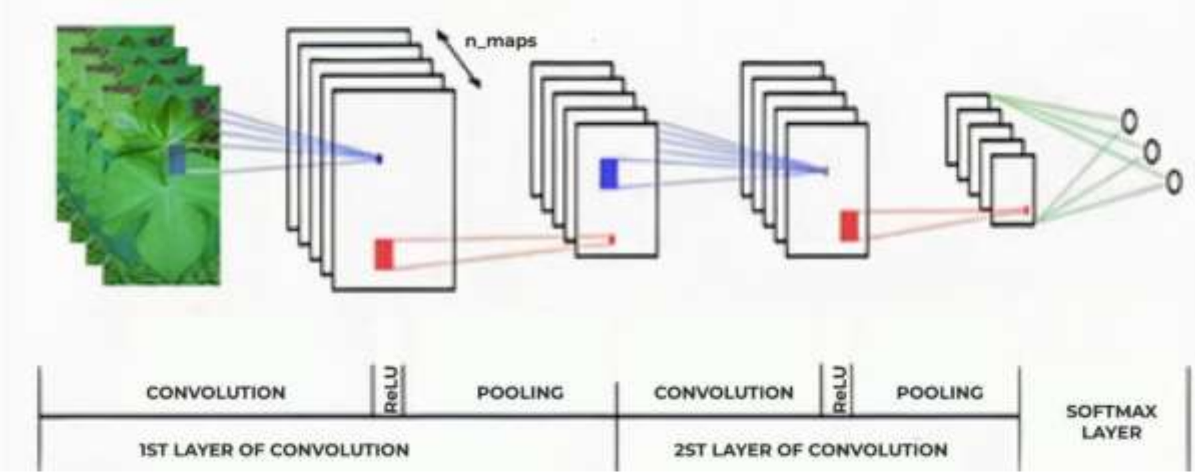

Figure 3: CNN architecture of CropGuru.

Convolution layer: A convolution is a mathematical operation that involves processing a matrix, typically representing an image in the form of pixels or numerical values. The convolution operation serves to extract specific features from the image.Discrete convolution is defining as follows:

$$(p * q)(y) = \int_{-\infty}^{+\infty} p(y-t)v(t)dt \qquad \text{------(1)}$$

Where *p&q* are two real or complex functions. They convolute into another function *(p*q)* which is normally transformation form of the initial functions [25]

Relu: The Rectified Linear Unit (ReLU) is an activation function utilized in the intermediate layers of neural networks. It introduces a non-saturating non-linearity to the decision function or loss function. ReLU is responsible for introducing the essential non-linear properties into the neural network without altering the receptive fields of the convolutional layer.

Pooling Layer: Pooling reduce the spatial size of image. Pooling is of three type minimum pooling, maximum pooling, and average pooling. Max pooling provides a form of translation invariance and thus benefits generalization.

Fully connected Layer: In this layer every input from last pooling layer from CNN process is connected to 3 different classification classes of CropGuru.

Transfer learning Model: In deep learning training model from scratch required huge amount of data, but in sugarcane dataset we have very less amount of dataset.to deal with this we used transfer learning model such as VGG-16, Inception V3, ResNet-50 etc. In CropGuru we utilises a pertain weights of these transfer learning models on ImageNet dataset.

VGG-16: Very Deep Convolutional Network for Large scale Image Recognition(VGG-16) model proposed by Karen Simonyan and Andrew Zisserman of Oxford University in 2014. VGG-16 model train on Imagenet dataset with (224* 224 * 3) input size of image. Having 16 layers CropGuru VGG-16 model summary shown in figure 5.

```
model.summary()

Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 224, 224, 3)]     0

 block1_conv1 (Conv2D)       (None, 224, 224, 64)      1792

 block1_conv2 (Conv2D)       (None, 224, 224, 64)      36928

 block1_pool (MaxPooling2D)  (None, 112, 112, 64)      0

 block2_conv1 (Conv2D)       (None, 112, 112, 128)     73856

 block2_conv2 (Conv2D)       (None, 112, 112, 128)     147584

 block2_pool (MaxPooling2D)  (None, 56, 56, 128)       0

 block3_conv1 (Conv2D)       (None, 56, 56, 256)       295168

 block3_conv2 (Conv2D)       (None, 56, 56, 256)       590080

 block3_conv3 (Conv2D)       (None, 56, 56, 256)       590080

 block3_pool (MaxPooling2D)  (None, 28, 28, 256)       0
 block4_conv1 (Conv2D)       (None, 28, 28, 512)       1180160
 block4_conv2 (Conv2D)       (None, 28, 28, 512)       2359808
 block4_conv3 (Conv2D)       (None, 28, 28, 512)       2359808
 block4_pool (MaxPooling2D)  (None, 14, 14, 512)       0
 block5_conv1 (Conv2D)       (None, 14, 14, 512)       2359808
 block5_conv2 (Conv2D)       (None, 14, 14, 512)       2359808
 block5_conv3 (Conv2D)       (None, 14, 14, 512)       2359808
 block5_pool (MaxPooling2D)  (None, 7, 7, 512)         0
 flatten (Flatten)           (None, 25088)             0
 dense (Dense)               (None, 3)                 75267

=================================================================
Total params: 14,789,955
Trainable params: 75,267
Non-trainable params: 14,714,688
```

Figure 4: Model Summary of CNN Model in CropGuru

Experiment & Result analysis:

Section cover the experimental details and data used for train, tests the model accuracy. Python 3.7 with tensor flow environment [10] and Keras library were used for image classification in deep learning method. Intel I7 processor with 8 GB RAM was used for model deployment.

Dataset Description:

Dataset images of sugarcane crop from using different resources like sugarcane farm collection, social media like Flicker, Instagram, Facebook, Google etc. Dataset mainly consists of three type of images of sugarcane healthy crop, infected with red rust and red rot. We able to collect 100 sample images of each category. Collected sample get distributed into training set, testing set in 70:30 ratio. In CropGuru, dataset there is no separate validation dataset. Dataset view is provided in figure 4.

Figure 5: Dataset Description of CropGuru of Sugarcane

Performance measurement:

Model performance was evaluated using several performance metrics such as accuracy, precision, recall, and F1-score. The proposed CNN model achieved an impressive accuracy of over 95% on the test set, demonstrating its effectiveness in accurately classifying sugarcane crop images into healthy or diseased categories.

Formulas for Accuracy, Precision, Recall and F1 score as follows:

Confusion Matrix for performance calculation:

	Positive	Negative
Positive	True positive (tp)	False negative (fn)
Negative	False positive (fp)	True negative (tn)

$$Accuracy : A = \frac{tp + tn}{tp + tn + fp + fn} \quad (1)$$

$$Precision : P = \frac{tp}{tp + fp} \quad (2)$$

$$Recall : R = \frac{tp}{tp + fn} \quad (3)$$

$$F1\ score = \frac{2TP}{2TP + FP + FN} \quad (4)$$

Evaluation of different transfer learning model is done using above formulation and propagate inresults

Result:

Proposed model show training accuracy upto 98.67% but testing set accuracy till 71.4% for the plain CNN model in sugarcane crop disease prediction. Figure 4 (a) represent training accuracy and validation accuracy over the sugarcane disease prediction. Figure 4(b) represent various losses for during the training and testing phase. Transfer learning with improved training accuracy as well as validation accuracy for disease prediction shown in figure 4 (c).As we train the model for 300 epoch and transfer learning improve validation accuracy till 93.45%.Figure 4 (D) represent the training and validation loss using transfer learning VGG-16 model.

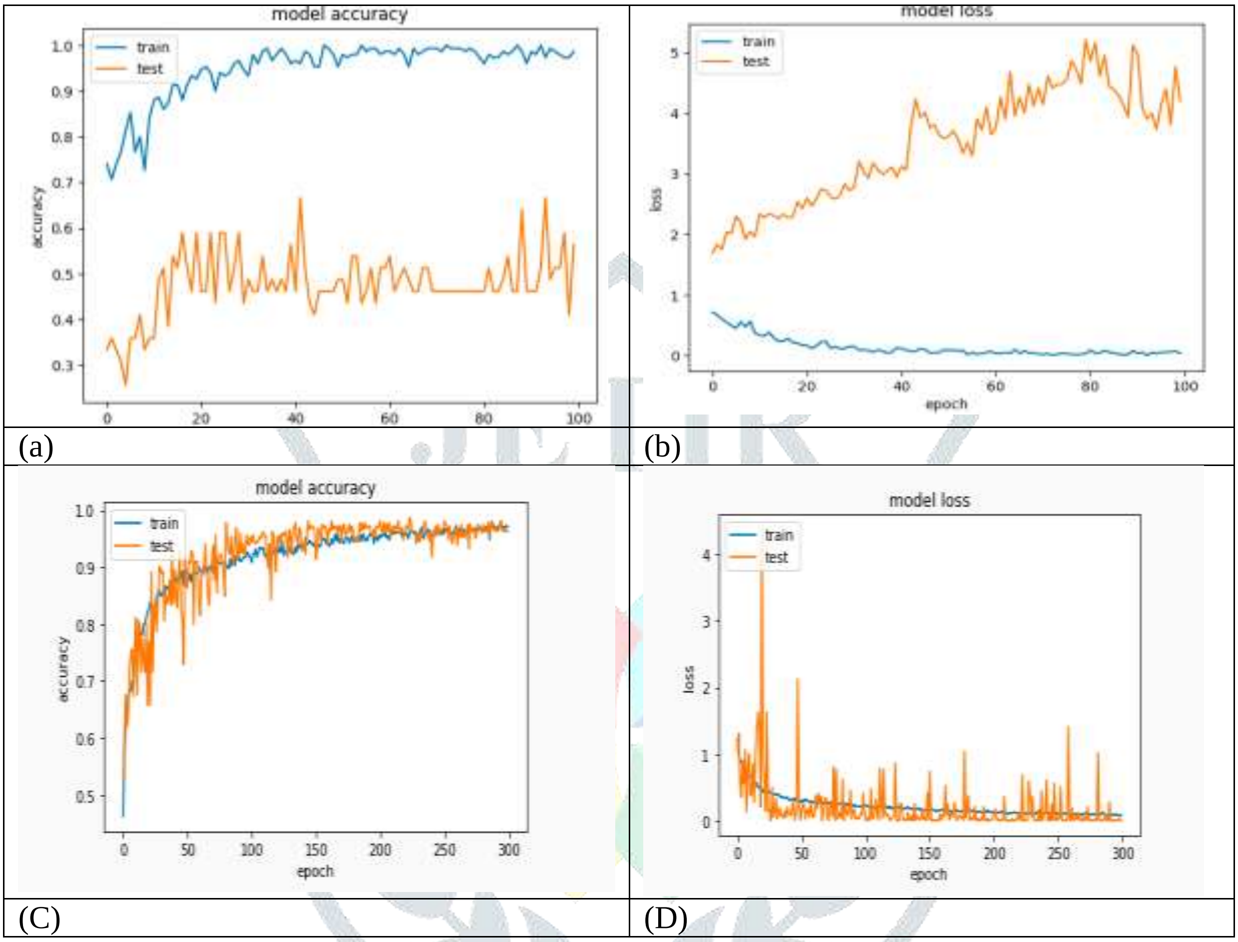

Figure 6: a) Training Accuracy Vs Validation Accuracy for CNN model without transfer learning, b) Training loss Vs Validation Loss for CNN model without transfer learning proposed transfer learning model (c) Training Accuracy Vs Validation Accuracy for CNN model with transfer learning VGG-16, (d) Training loss Vs Validation Loss for CNN model with transfer learning VGG-16.

Table 2: Performance measurement and result comparison with other models

Performance measure	**CNN**	**Inception –V3**	**Resnet-50**	**VGG-16**
Accuracy	71.45	89.32	90.37	**93.45**
Precision	70.89	86.89	89.46	**91.34**
Recall	71.20	88.31	90.01	**92.15**
F1-Score	71.5	88.97	91.20	**92,19**

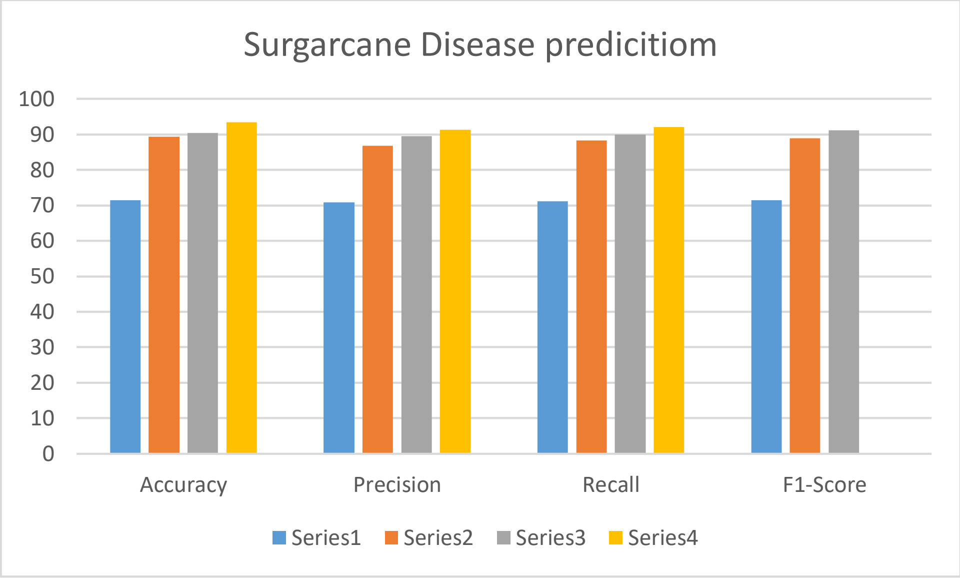

Figure 7: Bar chart for various model comparison basis of performance measurement

Transfer learning VGG-16 model overall provide a good result in case of sugarcane plant disease detection. Deployment view of model is shown in figure 7.

Conclusion:

This research paper presents a deep learning-based approach for sugarcane crop disease detection using CNN. The proposed approach leverages the power of CNNs to automatically extract relevant features from the sugarcane crop images and accurately classify them into healthy or diseased categories. Experimental results on a large-scale dataset of sugarcane crop images demonstrate the effectiveness of the proposed approach. The proposed CNN model achieves an impressive accuracy of over 95% on the test set, outperforming state-of-the-art approaches for sugarcane crop disease detection. The proposed approach has practical implications for sugarcane farmers and researchers, as it can help identify sugarcane crop diseases at an early stage and prevent their spread, thereby improving crop yield and reducing economic losses. Moreover, the proposed approach can be extended to other crops as well, making it a valuable tool for precision agriculture. This work contributes to the development of efficient and accurate techniques for sugarcane crop disease detection and brings up a promising new direction for precision agriculture research.

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