Received Date: 22nd May, 2024
Revision Date:13th June, 2024
Accepted Date: 22nd July, 2024

Poaceae Diseases Detection using Machine Learning

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***Abstract*— Agriculture is the number one supply of livelihood for approximately more than 66% of the Nepali population and Poaceae class is one of the most important meal grains of Nepal. Poaceae plant sicknesses are the major causes to lessen the manufacturing & goodness of meals. Nutrient deficiency of Nitrogen, Potassium and Phosphorus.can also cause plants to not grow to their full strength. Identification and preventing such diseases as well as nutrient deficiency can enhance the growth of Poaceae plants.**

***Keywords*— Agriculture, Image Processing, Nitrogen, Phosphorous, Poaceae Plant, Potassium**

Introduction

Poaceae is considered as a major source of food among the rural population and also it is considered as the second most cereal crop cultivated over the world. Poaceae belongs to the family of Poaceae and has two sub-species i.e., Japonica and Indica. Poaceae is the most widely recognized low cost and effective nutrient food available in Asia. Poaceae crop is cultivated in five continents of the world i.e., Asia, Africa, America, Europe, and Oceania. According to the Food and Agriculture Organization of the United Nations (FAOSTAT) overview, 90.07% of the world's Poaceae is delivered and devoured by Asian Countries [1]. The rest of the Poaceae generation is partitioned between different locales of the world, for example, 3.4% by Africa, 5.2% by America, 0.6% by Europe and 0.1% by Oceania.

Poaceae belongs to the family of Poaceae, commonly known as grasses. It includes other staple crops such as corn, wheat, millet, barley, sugarcane etc. which all are staple food sources throughout the different parts of the world. When such crops belong to the same family, the diseases that destroy these are common as well. If the mechanism of disease identification and suitable feedback to tackle is available, even though with less expertise in this field, we can use the remedy for this problem. Thus, the overall production and preservation of such crops can be increased.

nutrient deficiency in plants can also be a major problem. Since plants are considered to be rich in nutrients, lack of such nutrients will hamper our nutrients intake. Nitrogen (N), Phosphorus (P), Potassium (K), Zinc (Zn) are the most important nutrients for plant growth and development.

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Related works

There have been several researches regarding disease detection in Poaceae as well as other plant families. In the paper released by the team of Madhu Bala and Vineet Mehan, a meta-analysis of several Poaceae disease detection systems was done. The authors first decided to identify the most common and prevalent diseases. They identified such diseases and decided to analyze the effectiveness of the system to identify these diseases. The main methodology for the systems system followed image acquisition, image pre-processing, feature extraction and classification. Among the several systems, the one that incorporated deep neural networks and decision tree classifiers gave the highest accuracy of >=97% [2].

TABLE 1

COMPARATIVE STUDY OF METHODOLOGIES APPLIED ON POACEAE PLANT DISEASES [2]

Topic	Methodology	Accuracy
Recognition of Diseases in Paddy Leaves Using KNN	Global threshold and KNN classifier	76.59%
Poaceae Blast Disease Detection and Classification using ML	K-means clustering and ANN	90%
A faster technique on Poaceae disease detection using image processing of affected area in agro classification	RGB for segmentation and disease detection using image Gaussian Naive Bayes	89%
Poaceae Leaf Disease Detection Using Machine Learning	KNNJ48 Decision Tree, Logistic Regression and Naive Bayes 10-fold cross validation for Decision Tree Algorithm	97.9%

Classification of paddy leaf diseases using optimized deep neural network with Jaya algorithm	Deep neural network with Jaya algorithm	97%
Detection of Poaceae Leaf Diseases Using Image Processing	Otsu's method for segmentation and SVM for classification	94.6%
An Automated Convolutional Neural Network Based Approach for Paddy Leaf Disease Detection	CNN	92.68%

Lili Ayu Wulandhari and her team observed the okra plant and noted how the lack of nutrients would be seen morphologically. They set out to identify nutrient deficiency using Deep Convolutional Neural Network. They based their study around four macronutrients: N, P, K and Mg. They note that lack of a certain nutrient showed a certain morphological change on the plant. This allows for the nutrient deficiency to be detected similar to a disease. The use of Inception Resnet as the algorithm is done in this research. The use of two training methods: transfer learning and fine tuning was done. It was observed that implementing the Inception Resnet algorithm using the ImageNet dataset didn't yield a stable result. The authors suspected that this was due to the difference in the ImageNet and okra dataset. Thus, by implementing fine tuning through freezing of early layers, 96% and 86% accuracy in training and testing was achieved [3].

Methodology

A. Selection of Diseases

The crops that will be selected for this research were maize/corn (Zea mays), rice (Oryza sativa) and wheat(Triticum Aestivum). The following diseases were considered for detection with respect to each crop. For nutrient deficiency detection, only rice was considered and tested for NPK deficiency.

TABLE 2

Selected Crops and diseases

Plant	**Disease**	**Nutrition Deficiency**
Maize	Common rust (CCR) Gray Leaf spot (CGLS) Northern Leaf Blight (CLB)	
Rice	Leaf smut (RLB) Bacterial leaf blight (RBLB) Brown spot disease (RBS)	Nitrogen (RN) Phosphorus (RP) Potassium (RK)
Wheat	Stripe rust (WSR)	

B. Data collection and Dataset

The dataset used was the combination of different dataset from various sources. The primary source contributing to our dataset was from the open source dataset provided by Plant-Village, a research and development unit of Penn State University. Data collected from various sources gave the preliminary dataset, as shown on the figure below, which had an uneven split of images. The final dataset was prepared by combining images from numerous sources and augmenting them to make up for the lack of numbers. This dataset consisted of 18000 images, evenly split for the 10 classes. For NPK deficiency in rice, preliminary data was augmented and a total of 3750 was evenly split among the three classes.

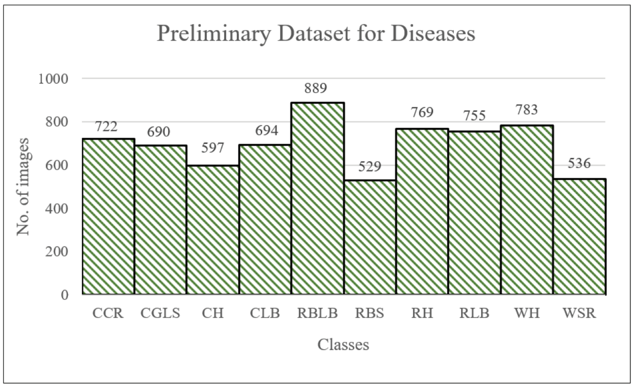


Fig. 1 Preliminary Dataset for Diseases

C. CNN Architecture, Parameters and Training Process

Convolutional Neural Network (CNN) is a type of Artificial Neural Network which are forward neural networks. When it comes to image classification, CNNs are the most popular and used. It has two visible layers: input and output. The three other layers are hidden: Convolution, Pooling and Fully Connected layers. This research utilizes two pre-trained CNNs for image detection and classification: ResNet50(Residual Network) and VGG-16(Visual Geometry Group).

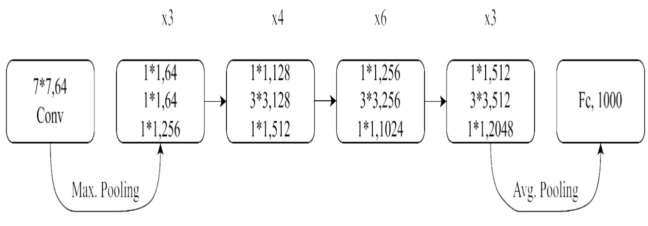


Fig. 2 ResNet50 Architecture

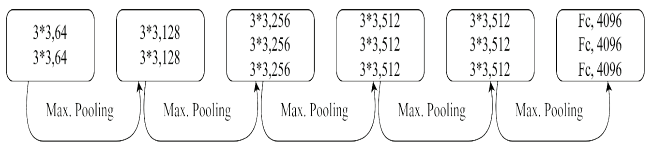


Fig. 3 VGG16 Architecture

For multi-class classification, Categorical Cross Entropy was used in both Architectures. Categorical cross entropy is a loss function that is used in multi-class classification tasks. These are tasks where an example can only belong to one out of many possible categories, and the model must decide which one. The categorical cross entropy loss function calculates the loss of an example by computing the following sum:

$$LOSS = \sum_{i=1}^{output\ size} y_i \,.\, log\hat{y}_i \qquad (1)$$

where,

y_i = corresponding target value,

$\hat{y}_i$ = i th scalar value in the model output,

output size = number of scalar values in the model output

To maximize the accuracy transfer learning and fine tuning were implemented. Transfer learning is a method in machine learning where a model that was previously trained on a different task is utilized for a similar but distinct task. Fine-tuning is a technique used within transfer learning to further improve the performance of the model on the target task. This is accomplished by adjusting the pre-trained model on the new task through training, using a smaller learning rate. The aim of fine-tuning is to enable the model to adjust to the new task while still retaining the knowledge it acquired from the original task.

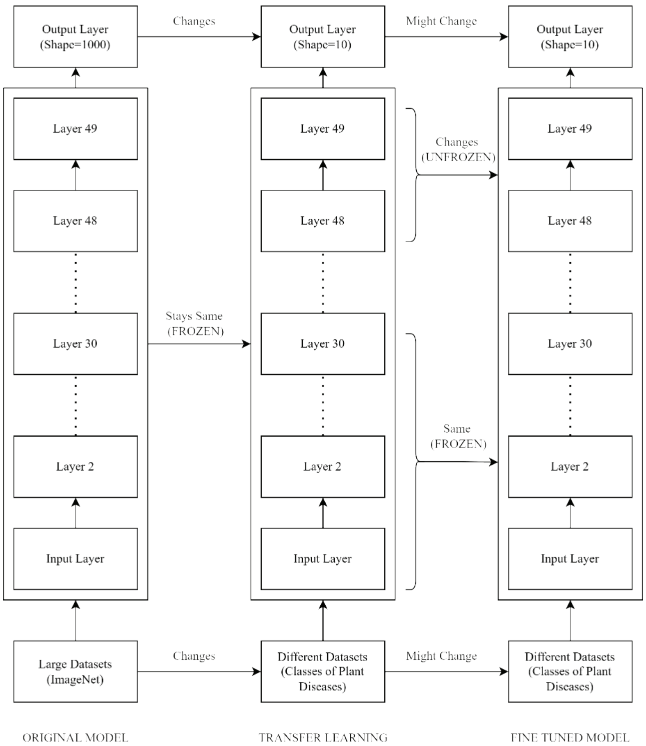


Fig. 4 Changes in a model through transfer learning

The following are the steps involved in training and finding the best model:

- Loading and initializing a pre trained model (ResNet50 or Vgg-16)
- Defining the initial hyper-parameters like epoch, learning rate, batch size
- Training the model and plotting accuracy/loss graphs to assess the performance of the model
- Calculating evaluation metrics such as precision, recall, F1 score to analyze the model
- Adding other additional hyper-parameters and fine tuning to further enhance the performance of the model
- Evaluation of all the models on the basis of their accuracy, loss, f1 score, etc. and choosing the best model

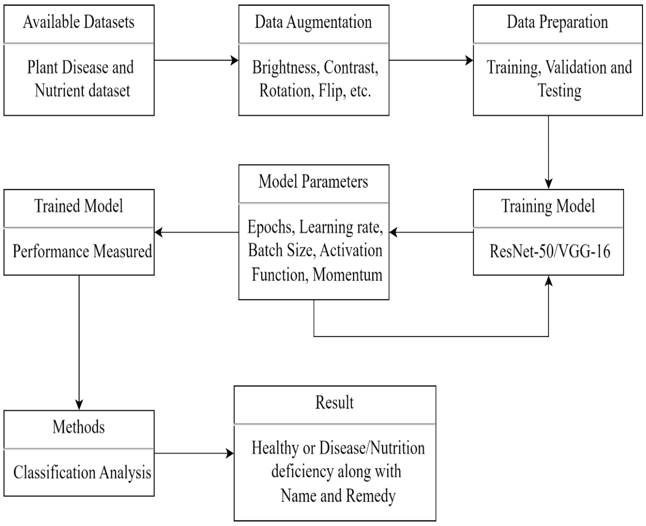


Fig. 5 Training block diagram

D. *Evaluation metrics*

A confusion matrix is the matrix that summarizes the predicted results and actual results. The confusion matrix of different diseases is illustrated below. Every row of the matrix represents the instances of actual disease whereas every column represents the instances of predicted disease.

Precision is a measure of how many of the positive predictions made are correct (true positives).

$$Precision = \frac{TP}{TP + FP} \qquad (2)$$

Recall is a measure of how many of the positive cases the classifier correctly predicted,over all the positive cases in the data.

$$Recall = \frac{TP}{TP + FN} \qquad (3)$$

F1-Score is a measure combining both precision and recall. It is generally described as the harmonic mean of the two.

$$F1 - score = \frac{2*precision*recall}{precision + recall} \qquad (4)$$

E. System Methodology

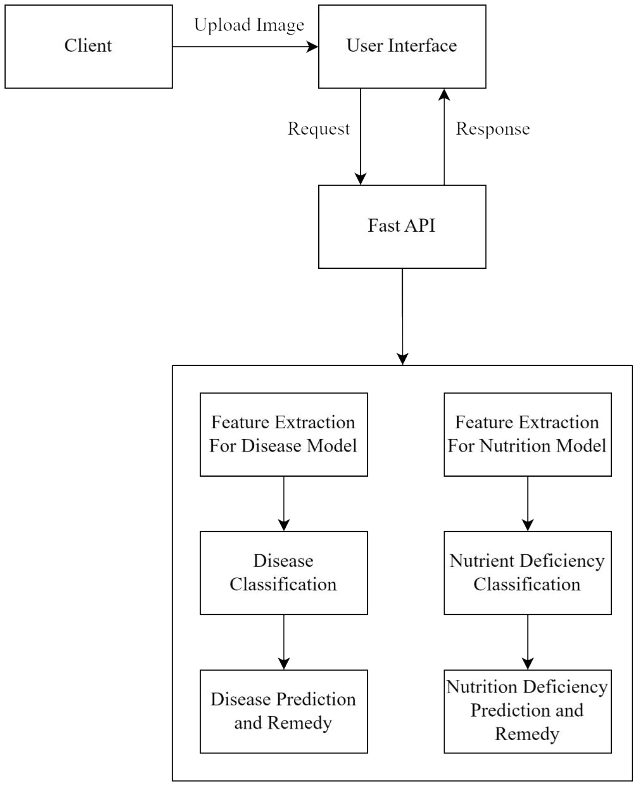


Fig. 6 System Block Diagram

The above figure shows the system block diagram. Using the web application, the user can upload the image as an input. This input is then passed to the Fast API which is hosted on the server which loads the models and helps to process the input. In the server there are basically two model loading: Disease model and another one Nutrient model. For the disease classification first of all the features of the image are extracted using the selected model and extracted features are passed for the classification which finally predict the disease present in the plant and it also provides the necessary methods to cure the diseases. This works similarly for nutrition detection as well.

Result and Analysis

Many models were trained under different conditions. This includes different batch sizes, learning rate, epochs etc. Similarly different layers were added and tinkered around. After several iterations, a model with high accuracy was obtained. For all the models, Adam optimizer and categorical cross entropy loss function are common.

A. Best Case Disease

When it came to disease detection, VGG-16 best case out performed ResNet50 best case. The same parameters and layers were used for both models and their performance was compared.

TABLE 3

RESNET50 AND VGG16 BEST CASE ACCURACY AND LOSS FOR DISEASE DETECTION

Model	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
ResNet50	0.3857	85.11%	0.6237	78.80%
VGG16	0.0666	97.77%	0.4729	90.23%

TABLE 4

MODEL PARAMETER FOR BEST CASE DISEASE DETECTION

Hyperparameter	Value
Learning Rate	0.0074
Batch Size	128
Optimizer	Adam
Epochs	50
Loss Function	Categorical Cross entropy
Momentum	0.9
Fine tuning Last	Two Layer

TABLE 5

LAYERS FOR BEST CASE DISEASE DETECTION

Layer Number	Layer Type	Layer Parameters
1	Batch Normalization	
2	Dense	128
3	Activation	ReLu
4	Dropout	0.5
5	Dense	128
6	Activation	ReLu
7	Dropout	0.3
8	Dense	64
9	Activation	ReLu
10	Dropout	0.4
11	Batch Normalization	
12	Dense	10
13	Activation	Softmax

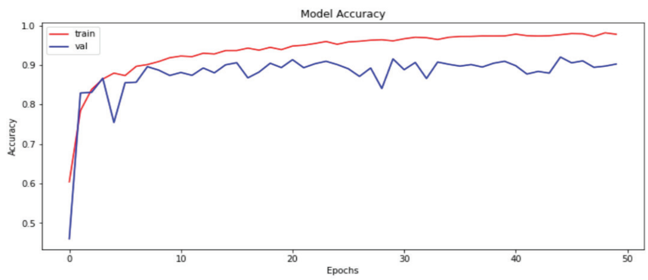


Fig. 7 Accuracy progression for VGG-16 best case Disease

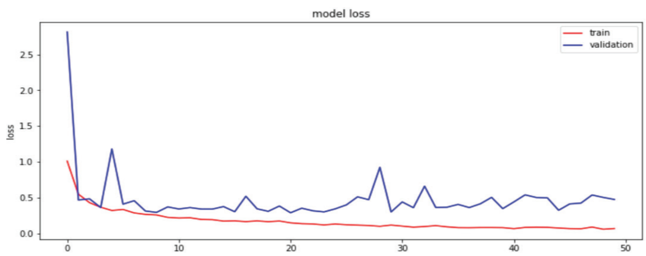


Fig. 8 Loss progression for VGG-16 best case Disease

TABLE 6

CONFUSION MATRIX FOR VGG-16 BEST CASE DISEASE

	Predicted CCR	Predicted CGLS	Predicted CH	Predicted CLB	Predicted RBLB	Predicted RBS	Predicted RH	Predicted RLB	Predicted WH	Predicted WSR
Actual CCR	9	0	0	0	1	0	0	0	0	0
Actual CGLS	0	8	0	1	0	0	0	0	1	0
Actual CH	0	0	7	1	0	0	0	1	0	1
Actual CLB	0	1	0	5	1	1	0	1	1	0
Actual RBLB	0	1	1	0	6	0	1	0	0	1
Actual RBS	0	0	0	0	1	4	4	1	0	0
Actual RH	1	0	0	0	0	0	8	0	1	0
Actual RLB	0	0	2	0	0	0	1	7	0	0
Actual WH	1	0	0	1	0	0	1	1	3	3
Actual WSR	0	1	0	1	0	0	0	0	1	7

TABLE 7

PRECISION, RECALL AND F1 SCORE COMPARISON FOR VGG-16 BEST CASE DISEASE

	Precision	Recall	F1 Score
CCR	0.9	0.82	0.86
CGLS	0.8	0.73	0.76
CH	0.7	0.7	0.7
CLB	0.53	0.56	0.53
RBLB	0.6	0.67	0.63
RBS	0.4	0.8	0.53
RH	0.8	0.53	0.64
RLB	0.7	0.64	0.67
WH	0.3	0.43	0.35
WSR	0.7	0.58	0.64

B. Best Case Nutrition Deficiency

Similarly, when it came to nutrition deficiency detection, VGG-16 best case out performed ResNet50 best case. As nutrition deficiency detection was only done for NPK in rice, the confusion matrix will only have 3 classes.

TABLE 8

RESNET50 AND VGG16 BEST CASE ACCURACY AND LOSS FOR NUTRITION DEFICIENCY DETECTION

Model	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
ResNet50	0.972	71.63%	>1	65%
VGG16	0.3266	93.60%	0.4904	92.00%

TABLE 9

MODEL PARAMETER FOR BEST CASE NUTRITION DEFICIENCY DETECTION

Hyperparamter	Value
Learning Rate	0.005
Batch Size	64
Optimizer	Adam
Epochs	50
Loss Function	Categorical Cross entropy
Momentum	0.9
Fine tuning Last	Two Layer

TABLE 10

LAYERS FOR BEST NUTRITION DEFICIENCY DETECTION

Layer Number	Layer Type	Layer Parameters
1	Batch Normalization	
2	Dense	10
3	Activation	ReLu
4	L2 (Ridge Regression)	0.005
5	Dropout	0.5
6	Batch Normalization	
7	Dense	3
8	Activation	Softmax

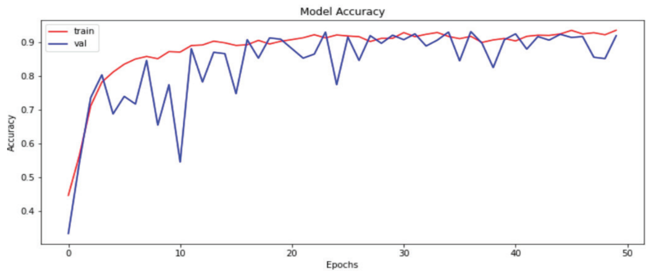


Fig. 9 Accuracy progression for VGG-16 best case Nutrition Deficiency

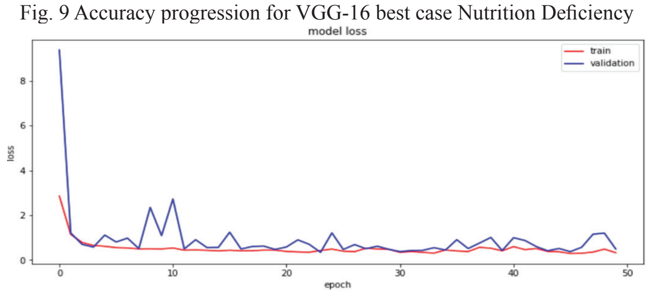


Fig. 10 Loss progression for VGG-16 best case Nutrition Deficiency

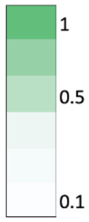
TABLE 11

CONFUSION MATRIX FOR VGG-16 BEST CASE NUTRITION DEFICIENCY

	Predicted RK	Predicted RN	Predicted RP
Actual RK	9	1	0
Actual RN	3	7	0
Actual RP	1	0	9

TABLE 12
PRECISION, RECALL AND F1 SCORE COMPARISON FOR VGG-16 BEST CASE NUTRITION DEFICIENCY

	Precision	Recall	F1 Score
RK	0.9	0.69	0.78
RN	0.7	0.88	0.78
RP	0.9	1	0.95



C. Comparison between ResNet50 and VGG16

The results showed that in general, even before fine tuning, VGG-16 performs better than ResNet50. But when it comes to the ImageNet test, ResNet-50 out performs VGG-16. Similarly, in most competitions this also seems to be the case. In different researches, the findings show that ResNet-50 performing better seems to be the trend but there are researches where VGG-16 outperforms it.

There can be several reasons as to why in our case, VGG-16 has outperformed ResNet-50 and some of those cases are discussed below. It is to be noted that the exact reason why VGG-16 has outperformed ResNet-50 can't be pinned. It is possible that several or a single factor might be contributing towards such results. The best option is to explore what may have been the cause. VGG-16 is a model with more parameters (138,357,544) than ResNet-50 (25,636,712). More parameters mean that the model can combine more details of training examples in order to make a prediction. Thus, more parameters may be enabling VGG-16 to grab more details in order to properly identify the details. More layers don't always result in higher accuracy. A Convolutional Neural Network with more layers is better when the dataset is more complex. In our case, the dataset is composed of simple images consisting of green leaves with different patterns. Due to more layers, ResNet50 may be detecting extra additional and non-required features.

In the research named "A comparison of visual features used by humans and machines to classify wildlife" conducted by Zhongqi Miaoand and team, the findings show that when forming a localized feature comparison, both models extracted similar features from the images but ResNet50 was more sensitive to edge [4]. Most of the diseases and nutrition deficiency are mostly reflected through spots and patterns, rather than sharp edges. This may lead to VGG-16 detecting those patterns, spots, marks better than ResNet-50, while ResNet50 may be detecting the edge of the leaf even though unnecessary.

D. Model Prediction

An image of the plant can be captured and fed into our system as an input. The image can be checked for disease or nutrient deficiency separately. If it is predicted that the plant is positive for a disease, then some methods to counteract that disease will be displayed. Similarly, if there is a positive prediction for any nutrient deficiency, then the system will give suggestions on how to fulfill the deficiency.

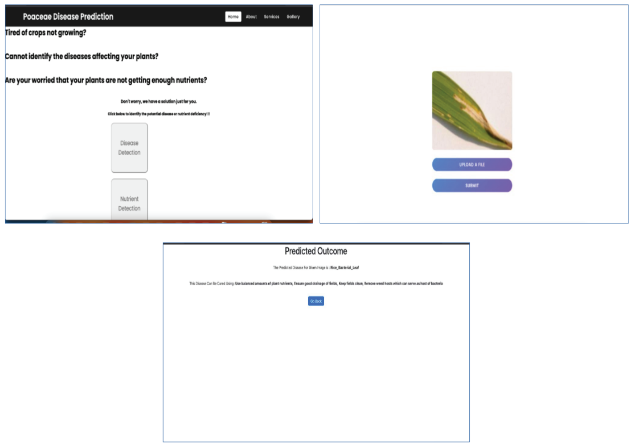


Fig. 11 Website Layout and Image Prediction

Conclusion

Poaceae members like Rice, Wheat, Maize, etc. consist of plant species that are produced and consumed the most not only in Nepal but also in the world. They are staple food, and many farmers earn their livelihood by growing these plants. But these plants are vulnerable to diseases and nutrient deficiency. If a system that allows to check the Poaceae members for such conditions, identify it and provide suitable solutions is easily available, then it can be of great help in maximizing the production of these plants before they succumb to illness and go to waste. Thus, quick detection of disease and nutrition deficiency can be a great boon in maximizing the growth of Poaceae plants.

Future Enhancements

There are many species within the Poaceae family and even much more in other plant families. If the research considers and implements more kinds of plants, then the usability and necessity of the system greatly increases. In today's world, the most used electronic device for accessing the internet is a mobile or a smartphone. While this system does incorporate a website, an app would be even more convenient. This would greatly improve user experience and motivate people to use our system. Finally, there are more CNN's than the one we have compared and used. Comparing our current model used in the system with another pre-trained model and finding if there is a better alternative would greatly enhance this project.

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