Crop Disease Classification of some Economically Important Crops in Nepal

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***Abstract*— Every year, the agricultural production in Nepal suffers due to various factors reducing the crop yield. Crop diseases are one of the prominent reasons for this. These diseases range from mild to causing massive destruction of crops. Despite the damages to crop yield, efforts to tackle this by leveraging Machine Learning techniques are rather sparse in Nepal. In this paper, we look at how effective some of the popular Deep Learning architectures as well as classical Machine Learning techniques (Logistic Regression, and Support Vector Machines (SVM) with Histogram of Oriented Gradients (HOG) feature descriptors) are at classifying plant diseases, while primarily focusing on the major crops (Rice, Maize, Potato, and Tomato) and their primary diseases in Nepal. We also look at some ways to gather image datasets for such problems.**

Keywords—Nepal crop diseases, deep learning, machine learning, image classification, crop disease classification

I. Introduction

Nepal, being primarily an agricultural country, has around 66 percent of its population engaged in farming; according to the Food and Agricultural Organization [1]. Despite so many people being involved in agriculture, Nepal imported around NRs. 22.24 billion worth of rice (which is the most produced crop in Nepal) according to the Nepal Foreign Trade Statistics in the fiscal year 2019/20 [2]. From the same source, we can find that other crops being imported besides rice are also some of the major crops produced in Nepal.

Some efforts like [4] and [5] have been made to classify a few such diseases in Nepal, which discuss about classification of a few diseases in Rice and Tomato respectively. However, a lot of other important diseases haven't been covered. In this paper, we want to focus on classification of some of the most prominent and destructive diseases in the major agricultural crops Nepal. This is with an aim to encourage smart agriculture and use of technology in agriculture in Nepal – the area where it is significantly behind some of the advanced nations.

II. Related Work

From what we found, most of the work related to classification of crop diseases is done on the PlantVillage Dataset. Papers like [6] and [7] discuss the use of pretrained deep learning models like AlexNet and GoogLeNet on this dataset. In [8], the authors present CropDeep, which is a large project where they create a huge crop dataset and run deep learning architectures on them for classification related tasks. They also present potential application of YOLOv3 in agricultural detection tasks. Similarly, in [9] the authors have presented the use of SVM with HOG feature descriptors to classify tomato and maize diseases.

In the context of Nepal, in Reference [4], the authors show how they use Twin Support Vector Machines (TSVM) for classification of Blast and Bacterial Blight of Rice with an accuracy of about 96%. Likewise, in [5], we see the use of CNN and YOLO models to classify Tomato diseases like Late Blight, Gray Spot, and Bacterial Canker with a relatively small dataset.

III. Crop Selection & Dataset Preparation

A. Selection of Crops and Diseases

The Statistical Information on Nepalese Agriculture released by the government lists all the major crops grown in Nepal by their area and production during the period of 2016-2019 [3]. The first task was to come up with the most important crops and their diseases. Based on literature review, and statistics released by the government, we decided to work on the following crops:

1) Rice (Paddy)

Rice has been the most important crop in Nepal since a very long time [10]. It has a huge impact on Nepal's economy and its consumption per capita here is among the highest in the world. Reference [11] discusses how the per capita of rice is about 137.5 kg, but the growth in productivity in the last 54 years is sitting at around 1.5%. With these reasons, Rice was naturally the first crop to work on such a classification problem.

Talking about the diseases, we went through several research papers to select the major diseases affecting rice in Nepal. Fungi seem to be the primary cause for most of the destructive rice diseases. Reference [12] shows the major fungal diseases in rice. Among the diseases presented, we had initially selected Fungal Blast, Brown Spot, Sheath Blight, and Sheath Rot, in order of severity. Most of these diseases are also known to be destructive throughout the world. However, we were not able to gather datasets for all these diseases, so, we picked only the "Fungal Blast" and "Brown Spot". Similarly, [13] discusses about "Bacterial Leaf Blight" causing losses of around 5-60% in some places. Likewise, we learned from [14] about the destructive “Rice Tungro” disease caused by the Tungro virus.

Diseases selected: Fungal blast of rice, Brown Spot, Bacterial Leaf Blight, Rice Tungro.

Fig. 1. A Sample of Rice Dataset Images

2) Maize (Corn)

Maize is also an important crop in terms of production and agriculture in Nepal. The statistics released by the government [3] shows maize as the most produced cereal crop after rice. Reference [15] provides a detailed overview of the important maize diseases and their management in Nepal. Among these, we picked “Gray Leaf Spot”, “Leaf Blight”, “Ear Rot”, “Head Smut”, and “Common Rust”, which were mentioned as the most economically important maize diseases in the article.

Diseases Selected: Gray Leaf Spot, Leaf Blight, Ear Rot, Head Smut, and Common Rust

Fig. 2. A Sample of Maize Dataset Images

3) Tomato

Tomato consumption, while not as high as rice, is still high at around 12 kg/person per year despite around 78.2% of it being imported [16]. It is one of the economically important crops.

“Late Blight” is one of the most serious diseases of tomato and potato worldwide causing losses of up to 100% in some cases [17]. Similarly, the “Tomato Leaf Curl Virus” is said to cause yield loss of up to 40% in some areas [18]. We also selected “Bacterial Spot of Tomato” despite it not being as devastating and prevalent as the rest, albeit still being present in Nepal, and for which we found a good dataset [19].

Diseases selected: Bacterial Spot, Early Blight, Late Blight, Tomato Yellow Leaf Curl Virus

Fig. 3. A Sample of Tomato Dataset Images

4) Potato

The government’s statistics [3] also shows potato to be one of the highest produced cash crops (3,112,947 Metric Tons in the year 2018/19). References [20] and [21] mention how “Late Blight of Potato” is one of the most devastating diseases of potato and highlight the need to control it. While we found that Bacterial Wilt was another important disease in potato, we could not get hold of a proper dataset.

Diseases selected: Early blight, Late blight

Fig. 4. A Sample of Potato Dataset Images

B. Gathering Data

1) Well-defined Datasets

Initially, to gather the data, we looked at some of the common crop disease datasets like the famous PlantVillage Dataset [29]. We were able to get images for Tomato and Potato from this dataset. For rice, we got two different types of datasets through [23] and [24]. The second dataset had very high-resolution images and we compressed them before training. For maize leaves, we found a good dataset on Kaggle [25].

2) Scrape mini-project (Maize Fruit)

We could not find a dataset for maize fruit diseases like Head Smut and Ear Rot. We also required a healthy maize dataset for better results. For this specific purpose, we worked on a small image scraping project.

We collected images from Google and DuckDuckGo search using the Selenium WebDriver and JMD Image Scraper library [26]. We then separated the first 15 images into a "Yes" folder, and then augmented the images. The last 150 images were put in a "No" folder (The idea here is that, usually, the image search results tend to give inappropriate results, particularly for an image classification task, towards the back end of the results and gives exactly what we want in the first few images. These can then be used to classify the middle group of images to prepare the dataset). A pretrained deep learning model (EfficientNet – b7) would then be trained on these images and it would put together all the images that we scraped into a single folder, giving us an almost-ready dataset for classification. We also used translated search terms, like Chinese and Spanish, to get more images (which also seemed effective). We are distributing this as an open-source project and can be accessed through [27].

IV. Methodologies

Before addressing the problem, we had to think about which Machine Learning techniques to use. The obvious answer was a pretrained deep learning model, but we also wanted to observe how some of the classical machine learning techniques would perform (as deep learning models would be computationally expensive, take longer to train, as well as be relatively expensive to deploy). As such, we looked at some of the common classification techniques – Logistic Regression and Support Vector Machines (SVM). Following this, we moved to using deep learning models starting with a rather simple CNN and gradually moving to more complex pretrained models such as the GoogleNet and EfficientNet-b7.

A. *Logistic Regression*

Logistic Regression is a process of modeling the probability of a discrete outcome given an input variable. Here we assume that the target is drawn from a Bernoulli distribution with parameter *p* being the probability of class 1:

$$y \sim Bernoulli(p) \tag{1}$$

The parameter *p* is a "squashed" linear function of *x*, i.e.,

$$p = sigmoid(\theta^T x) = g(\theta^T x) = \frac{1}{1+e^{-\theta^T x}} \tag{2}$$

In logistic regression, we train the model on training dataset to find the parameters θ that maximizes the following log likelihood function:

$$l(\theta) = \sum_{i=1}^{m} y^{(i)} \log\left(h_\theta(x^{(i)})\right) + \left(1 - y^{(i)}\right) \log\left(1 - (h_\theta(x^{(i)})\right) \tag{3}$$

We trained logistic regression models (1000 iterations) for each category of crops to classify their diseases on both grayscale images and using HOG features. The grayscale image array was basically the X matrix with the image labels being the y vector. These were split into 80% training and validation datasets to train the model and calculate the accuracy on the validation set respectively.

B. *Support Vector Machine*

Support Vector Machines (SVM) are supervised learning models with associated learning algorithm that analyze data for classification and regression analysis. SVMs are one of the most robust prediction methods based on statistical learning frameworks or VC theory.

Rather than maximizing the likelihood function like logistic regression, SVM maximizes the margin:

$$w^*, b^* = \underset{w,b}{argmax} \quad "minimum\ margin" \tag{4}$$

This margin could be either functional margin or geometric margin. The functional margin for example *i* is given by:

$$\gamma'^{(i)} = Y^{(i)}(w^T X^{(i)} + b) \tag{5}$$

Whereas the geometric margin for example i is given by:

$$\gamma^{(i)} = Y^{(i)}\left(\frac{w^T}{||w||} X^{(i)} + \frac{b}{||w||}\right) \tag{6}$$

An SVM training algorithm builds a model that assigns new examples to one category or the other, making it a non-probabilistic binary linear classifier.

In addition to performing linear classification, SVMs can efficiently perform a non-linear classification using what is called kernel trick, implicitly mapping their inputs into high dimensional feature spaces. One of the kernels is the Gaussian or radial basis function (RBF) kernel:

$$K(X,Z) = e^{\frac{-||X-Z||^2}{2\sigma^2}} \tag{6}$$

For non-separable data, it uses slack variables specifying how far into the margin a training example intrudes.

As with Logistic Regression, we used SVMs (both linear and RBF kernel) on the crop diseases. The X matrix and y vectors were the same as used for Logistic Regression. We set the "gamma" (sigma) parameter to scale according to the features. Likewise, we set the C value (the regularization parameter; this value of C basically determines the size of the margin of the hyperplane – if C is larger, the margin will be smaller) as 8.0, which gave better accuracy scores on the RBF kernel. Going beyond 8.0 to a larger value did not seem to improve the accuracy.

C. *Histogram of Oriented Gradients (HOG)*

Histogram of Oriented Gradients is a feature descriptor that is used to extract features from input image. The HOG descriptor focuses on the structure or the shape of an object by extracting the gradient and orientation of the edges. These orientations are calculated in 'localized' portions. After that, histograms are created using the gradients and orientations of the pixel values, hence the name 'Histogram of Oriented Gradients'.

First of all, horizontal and vertical gradients need to be calculated using the respective kernels. Then the magnitude and the direction of gradients is calculated using:

$$g = \sqrt{g_x^2 + g_y^2} \tag{8}$$

and,

$$\theta = \arctan\frac{g_y}{g_x} \tag{9}$$

respectively. Before moving on to the next step, the image needs to be divided into cells so that the histogram of gradients can be calculated for each individual cells. Now we convert these numbers to calculate histograms.

For the histogram, nine separate bins need to be created, each corresponding to angles from 0-160 in increments of 20 which represents the direction of gradients (0-180 degree). And based upon these direction values, the corresponding magnitude values are placed inside of the bin. After performing this process, a histogram can be formed, and the bins that have the most weight can easily be seen.

To make the descriptor to be devoid of lighting variations so that it becomes unbiased and effective, normalization can be done on each block.

The figure below is an example of extracted HOG feature from a diseased maize leaf.

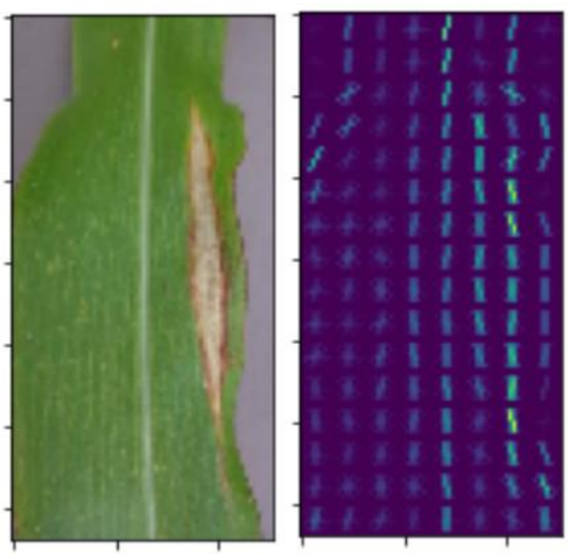

Fig. 5. Maize Leaf Blight HOG Feature Extraction

D. Deep Learning Models

For a start, we used a simple 5 layers of Convolutional Neural Network along with Batch Normalization blocks and drop out layer in between Convolutional layer, followed by 3 layers of Fully connected layers (including output layer) at the end.

The other two models that we used are: GoogLeNet and EfficientNet, both trained on ImageNet datasets (pretrained model).

a) GoogLeNet model: GoogLeNet is a Deep Convolutional Neural Network developed by Google. It is 22-layer deep CNN that is a variant of the Inception Network. This model is mostly used for Image Classification purpose and also for other computer vision tasks such as face detection and recognition, etc.

The GoogLeNet architecture consists of 27 layers including pooling layers, and part of these layers are a total of 9 inception modules, and a single linear layer with softmax activation function as a fully connected classification layer.

b) EfficientNet-B7 model: This is the other pretrained model that we used for our problem. We chose this particular model because of it's state-of-the-art acheivement (84.3% top-1 accuracy on ImageNet), while being 8.4 times smaller and 6.1 times faster on inference than the best existing ConvNet [28]. In addition to that, this model also transfers well and acheives state-of-the-art accuracy on CIFAR-100, Flowers and 3 other learning datasets, with an order of magnitude fewer parameters.

Another important reason of chosing this particular model is due to its principled method to scale up CNNs to obtain better accuracy and efficiency, so that, in the future, if we have more resources available then we can scale up our model more effectively improving the overall model performace. This scaling method is called compound scaling.

The compound scaling method is based on the idea of balancing dimensions of width, depth, and resolution by scaling with a constant ratio. These equations show how it can be acheived mathematically:

$$Depth, d = \alpha^{\phi}, Width, w = \beta^{\phi}, Resolution\ r = \gamma^{\phi}, \tag{10}$$

such that,

$$\alpha.\beta^2.\gamma^2 \approx 2$$

$$\alpha \geq 1,\ \beta \geq 1,\ \gamma \geq 1$$

where, the values of α, β, γ are determined using a grid search algorithm. ϕ determines the increase in computational resources to the network. This parameter is user defined.

EfficientNet is based on the baseline network developed by the neural architecture search using the AutoML MNAS framework. The network is finetuned for obtaining maximum accuracy but is also penalized if the network is very computationally heavy. It is also penalized for slow inference time when the network takes a lot of time to make predictions.

This obtained baseline model is scaled up to obtain the family of EfficientNets.

V. Results

A. Classical Machine Learning Algorithms

The table below lists the accuracy scores we obtained while using the classical machine learning algorithms.

TABLE I. ACCURACY SCORES WITH CLASSICAL ML TECHNIQUES

	Accuracy Scores		
	Logistic Regression	***SVM (Linear) C = 8.0***	***SVM (RBF) C = 8.0***
Rice 1	91%	93%	97%
Rice 2	33%	34%	48%
Maize Leaf	69%	70%	76%
Maize Fruit (Scraped)	42%	43%	66%
Tomato	52%	52%	79%
Potato 1	82%	82%	76%
Potato 2	55%	53%	72%

We can note that only the “Rice 1” dataset allows these models to reach an accuracy score of above 90%. For every other dataset, these models seem to be impractical. Moving on, we looked for other alternatives after observing these values. The first thing that we tried was the use of HOG descriptors.

The following table lists the accuracy scores obtained using HOG features.

TABLE II. ACCURACY SCORES WITH HOG FEATURES

	Accuracy Scores		
	Logistic Regression	***SVM (Linear) C = 8.0***	***SVM (RBF) C = 8.0***
Rice 1	88%	91%	98%
Rice 2	51%	48%	58%
Maize Leaf	77%	76%	85%
Maize Fruit (Scraped)	60%	55%	76%
Tomato	80%	77%	85%
Potato 1	77%	75%	84%
Potato 2	74%	71%	79%

We can notice how using HOG features improved the accuracy score on most of the datasets for the RBF Kernel. With up to 98%, 85%, 85%, and 84% of accuracy scores respectively, the RBF SVM looks somewhat viable to classify the Rice 1, Maize Leaf, Tomato, and Potato 1 datasets. However, the other scores were still not good enough, which made us look at the deep learning models.

B. Deep Learning Models

The table below lists the accuracy scores we obtained using deep learning models.

TABLE III. ACCURACY SCORES WITH DEEP LEARNING MODELS

	Accuracy Scores		
	Simple Model	***GoogleNet***	***EfficientNet-b7***
Rice 1	88%	98%	99%
Rice 2	65%	92%	92%
Maize Leaf	85%	98%	99%
Maize Fruit (Scraped)	94%	99%	99%
Tomato	88%	99%	99%
Potato 1	89%	99%	98%
Potato 2	85%	98%	99%

As our simple model was not able to score very high (as low as 65%) compared to related works like [6] and [7] on the PlantVillage dataset, which discuss about using pretrained models such as GoogleNet and AlexNet, we decided to use pretrained models like these. We achieved a good accuracy score of about 99% for most of the crops with GoogleNet. We also tried Efficientnet-b7 to see if it could perform better on the Rice 2 dataset, however, the results were mostly like what we got using GoogleNet.

VI. Conclusions and Next Steps

To summarize, we ended up with good models to predict crop diseases if they come from a similar sample to our dataset. It is yet to be seen how well these models generalize on the real data generated by the potential users. Right now, it is difficult to test this on the real world because it is not the season for these crops to grow. While we did test some images of tomato leaves from our own garden, we are not sure if the images are being labelled correctly.

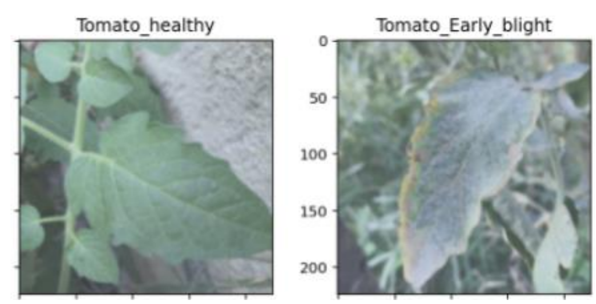

Fig. 6. Tomato Prediction Example

The next step, or further improvements to this project would be use of a larger and a proper dataset, that represents the data generated by the users, and adding more crops and diseases for classification. Getting data directly from NARC – the National Agricultural Research Center in Nepal would be preferred option. Another option would be to visit the fields to get the images, or, let the diseases flourish in a monitored lab environment for selected plants. As we have set up a proper structure to train the classifiers, we would only need these images placed inside labelled folders to train the model to make it more robust and generalize better to the real-world data.

Before concluding about the reliability of our solution, we want to observe how it performs in the real world. It would be convenient to deploy these models on IoT devices to automatically detect crop diseases and ultimately for the growth of smart agriculture, but it is not viable right now (in Nepal) as most agricultural sites are not making use of smart tools in agriculture yet. We thus plan to deploy a web application soon where the users would be able to upload images and get their crops classified. If we were to consider only about allowing users to get their images predicted, we would likely not need a huge data storage, however, as we seek to evaluate how our model performs with the help of experts, we need to be able to store and access this data to continually improve the performance. Thus, we are looking for viable options to deploy this project. Additionally, with expert advice, the deployed application could also be tailored to point the users to appropriate pesticides or other solutions to take care of their crops.

On another note, we worked on this project with a lack of expert domain knowledge and thus would like to discuss and improve our solution with an expert in this field. In particular, we seek assistance with the generalization of the model to real-world data generated by the users.

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