

INTERNATIONAL BACCALAUREATE DIPLOMA PROGRAMME

WORLD STUDIES EXTENDED ESSAY

Discipline: Computer Science and Economics

Topic: Enhancing Food Security in Ghana through Automated Plant Disease Diagnosis
using Machine Learning

Research Question: To what extent can machine learning and an automated plant disease diagnosis help to promote food security in Ghana?



Summary of Comments on Extended Essay

Page: 1

 Number: 1 Author: Lauretta Shardow Date: 12/09/2023 12:02:42 pm
Which of the 6 World Study areas does your EE fall under?

 Number: 2 Author: Lauretta Shardow Date: 12/09/2023 12:04:46 pm
The Enhancement of Food Security in Ghana through Automated Plant Disease Diagnosis using Machine Learning.

TABLE OF CONTENT

Introduction
Methodology
Data Collection
Computer Science
i. Convolutional Neural Networks.....
a) Pooling layer
b) Fully Connected layer
c) Input-Output Neuron
ii. Model Building and Training
a) MobileNetV2 architecture
b) SoftMax activation function
c) HyperParameter Tuning
ii. Model Testing
a) Prediction Using the Saved Model
Iii Evaluation and Metrics
Iv Confusion Matrix
Vi Limitation of Convolutional Neural Network Model
Economics
I What is Food Security
Ii Technology Adoption Theory
Iii Behavioural Economics
Iiii Cost-Benefit Analysis
V Economies of Scale
Vi Resource Allocation
Vii Risk Management
Evaluation
Conclusion
Works Cited
Bibliography
Appendix A

 Number: 1
Good outline

Author: Lauretta Shardow

Date: 12/09/2023 12:06:21 pm

Appendix B

Appendix C

Appendix D

Criterion A : Topic, Research question, Methodology

Criterion B : Context, Subject-specific terminology and concepts

Criterion C : Research, Analysis and Discussion and evaluation

Criterion D : Strands: Structure, Layout

Introduction

The world bank believes that if the trend in growth rate of population continues at the rate of 2.66%. The population of sub-saharan Africa including Ghana could be as large as 2.5 billion in 2050 (**Tessema and Fantahun**). Hence Ghana would have to increase food production to meet the demand of consumers of a growing population. In fact according to the Ghana Living Standards (2017), tomatoes make up the highest proportion of 11.6% of household vegetable consumption (**GHANA LIVING STANDARDS SURVEY REPORT of the FIFTH ROUND (GLSS 5)** *Ghana Statistical Service*)

. Many Ghanaian staple foods include tomato in preparation and as the population is rapidly growing, it is not surprising that the demand for staple crops like tomato will increase. Furthermore crop production serves as a profitable business and the potential area to increase livelihood of small scale farmers to produce large volumes to meet the demand. Unfortunately farmers face drawbacks in crop production from factors such as late plant disease detection. Plant disease is an alarming issue in the agricultural industry and has a huge impact on crop productivity. Hence if farmers detect the diseases at the early stage, it will help mitigate crop losses therefore resources will be efficiently utilized and no additional cost will be incurred for treatment of pest and diseases and post- harvest losses. The Ministry of Food and Agriculture (Ghana) goal is to “contribute to sustainable reduction in crop losses caused by pests and diseases which is currently estimated at 30-50%, to about 10-15% with substantially reduced use of hazardous chemicals” (**“Plant Protection & Regulatory Services”**). Therefore, the ministry

has embarked to educate local farmers on crop pests and disease management. The intervention in conjunction with subsidized fertilizers and improved seeds under the PFJ programme increased by 60%, from 18,333MT in 2019 to 29,500MT in 2020.

Even Though this solution will have an impact since farmers have knowledge in pest and disease management, its approaches to disease detection may be time-consuming and expensive, and not always accurate. Secondly the cost spent by the ministry of food and agriculture on pest and disease management could have been used for other activities which is an opportunity cost for instance to fund mechanized tools for farmers to increase their crop yield and productivity. The current manual process of diagnosing plant diseases is not only time-consuming but also prone to errors, and Diagnoses cannot be done on the large scale. Hence using machine learning to develop automated plant diagnoses can help mitigate the problem identified. In this research, I propose that a plant disease diagnosis developed from convolutional neural networks (CNNs) to identify diseases in real-time. This model relies on images uploaded by farmers and leveraging CNNs helps to learn and extract distinctive attributes from images by employing multiple layers of filters. Subsequently, these attributes from uploaded images are categorized whether the plant is healthy or not, the type of disease it has and recommendations to treat the plant. The system is specifically engineered to ensure minimal computational burden, allowing seamless deployment on real-time devices like smartphones which can be used by local farmers on the field. It is also cost effective, time-saving in nature, and precise outcomes render it highly appropriate for utilization.

Furthermore, This model can decrease the environment and human health issues concerning the widespread use of pesticides. Farmers can reduce the use of insecticides and pesticides by accurately finding the disease at the early stage before the disease increases widespread.

This helped me come up with a research question since machine learning can be a vital solution I can explore to address the issue of food insecurity.

To what extent can machine learning and an automated plant disease diagnosis help to promote food security in Ghana?

The research will draw knowledge from two disciplines, computer science and economics. In this case computer science will enable me to apply technical tools for creating machine learning systems using python, tensorflow and jupyter notebook for image processing and algorithm development.

Jupyter Notebook is a computing environment for live code and visualizations. I will be using python libraries such as Matplotlib, Scikit-learn, Numpy and pandas for developing machine learning models for data analysis.

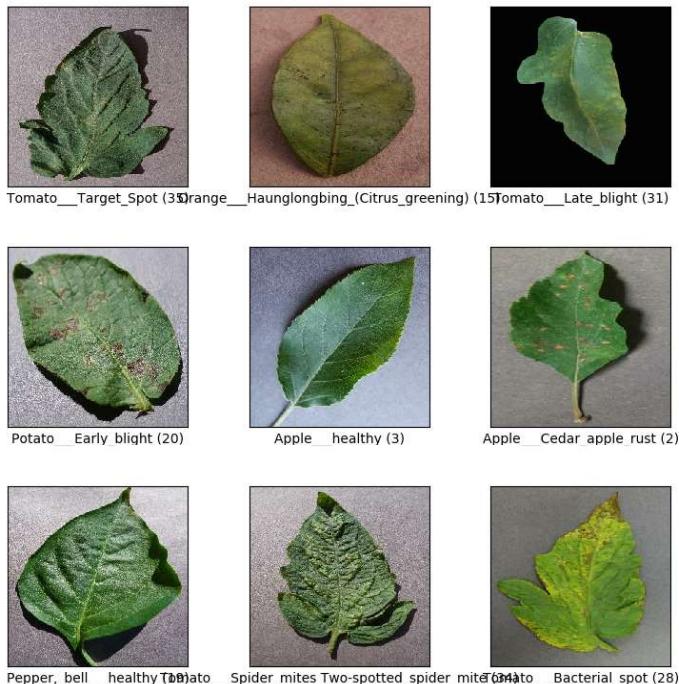
I also aim to use convolutional neural networks , a widely used deep learning model, to successfully analyze visual images which can readily be separated into the necessary characteristics. Lastly a workflow is introduced for our plant disease detection. This field of discipline will enable me to develop a system that farmers can use by uploading real time images to determine the conditions and health of plants. Secondly farmers will obtain recommendations on how to manage plants with diseases identified.

With regards to Economics, I am to highlight how crop disease diagnoses can efficiently allocate resources such as raw materials, land and capital in agriculture. To also evaluate the changes in the supply and demand equilibrium in the market and how prices will provide insights into economic impacts. Furthermore, I develop a cost-benefit analysis which will involve comparing the costs of implementing disease detection and management measures with the benefits gained from increased crop yields and food security. This will determine whether investment in disease detection systems is economically justified. Through incentives and behavioral economics, I will be analyzing how farmers respond to incentives for adopting disease detection systems and to explain decision-making patterns and design effective incentive structures. Lastly, we will consider how the proposed solution will increase productivity and to reduce crop yield loss and whether it will promote the increase in supply of food to meet the increasing demand of consumers. Food security can have a significant impact on poverty reduction and overall economic development and hence exploring how automated plant disease diagnosis can increase economic development in alleviating poverty for small-scaled farmers. Afterall, agriculture contributes to 54% of Ghana's GDP, and accounts for over 40% of export earnings, while at the same time also contributes to 90% of the food needs of the country.
(“Ghana at a Glance | FAO in Ghana | Food and Agriculture Organization of the United Nations”)

. Therefore it is important to evaluate the economic impact of the implementation of autonomous plant disease diagnosis since food is a major contributor to Ghana's GDP.

Methodology

In order to respond to my research question effectively to develop a plant disease detector, I used a secondary data which is the plant village data that contains various images of plants affected with diseases and viruses that are common in our crops in Ghana. Therefore, I researched various types of diseases in crops such as tomatoes, maize, orange, tomato, pepper and cocoa (<https://ipm.ucanr.edu/PMG/diseases/diseaseslist.html>) . I selected these crops since they are produced in large quantities to provide food for the country. Secondly cocoa is one of our main exports that brings income to the country and hence increases our economic growth. I obtained information from the ministry of agriculture on the measures and technology used for pest and disease management. I obtained my dataset of plant images with diseases both healthy and unhealthy for machine learning and deep learning to generate a model for plant disease detection. The dataset was obtained from Tensorflow which consists of 54303 healthy and unhealthy leaf images divided into 38 classes by species and disease (“**Plant_village | TensorFlow Datasets**”).



(Image Source:
Tensorflow)

The plant village dataset has images of 26 different types of plant diseases across crops selected which include tomato, orange, pepper, potato, yam, soybean and cocoa. Some of the diseases that were included are Black Rot, Bacterial Spot, Late Blight, Leaf Scorch, Early Blight,

Powdery Mildew and swollen shoot virus disease. These diseases are major infections found in Ghana and other West African countries that grow in crops (**Ofori et al.**).

Computer Science

What are Convolutional Neural Networks?

A convolutional neural network is one of the various types of neural networks in deep learning which is tailored to image recognition and processes that involve the manipulation of pixel-level information. They have the ability to identify and categorize objects. As a result, it is well-suited for algorithms related to computer vision, where accurately recognizing objects is crucial for plant disease detection.

Diagram of Convolutional Neural Network (figure 2)

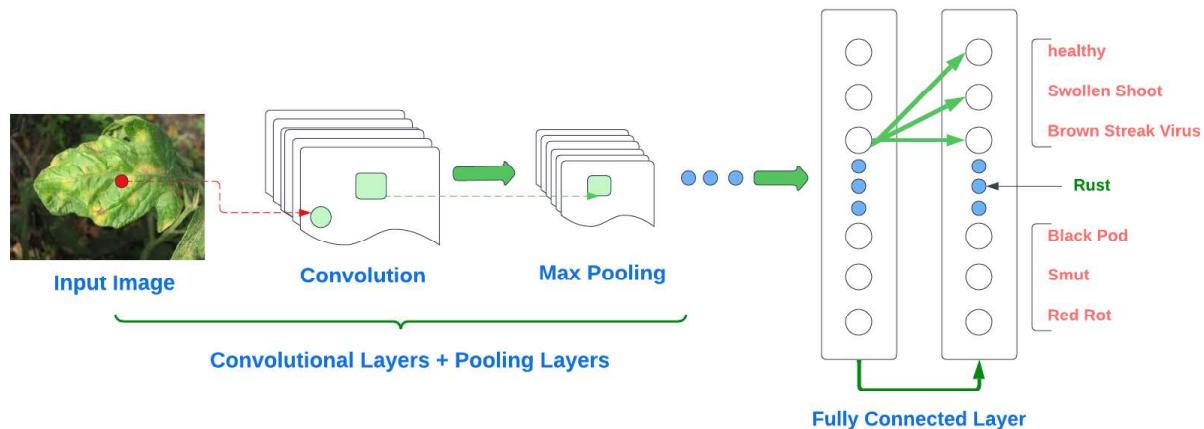


Figure 2 shows the diagram I used in building the convolutional neural network model. The CNN block requires a filter, input data and a feature map. From the diagram I used a color image labeled as ‘Input Image’ which is made up of pixels in 3D and hence dimensions will have a height, width and a length and that relates to RGB. Next, at the convolution process a filter

 Number: 1

Author: Lauretta Shardow

Date: 12/09/2023 12:07:02 pm

Source of diagram?

moves across receptive fields of the image to check if a feature is present. For instance a filter is applied to an area of the image indicated by a red dot. Then the selected dot area is fed into the output array. Then the filter shifts by a stride and continues until the kernel is swept until the entire image is processed.

Pooling Layer

The pooling layer runs over the entire input data then the kernel applies an aggregation function where it looks at the group of data segments and decides on one number to represent them. This way, we get a smaller set of numbers that still gives us a good idea of what is in the original data.

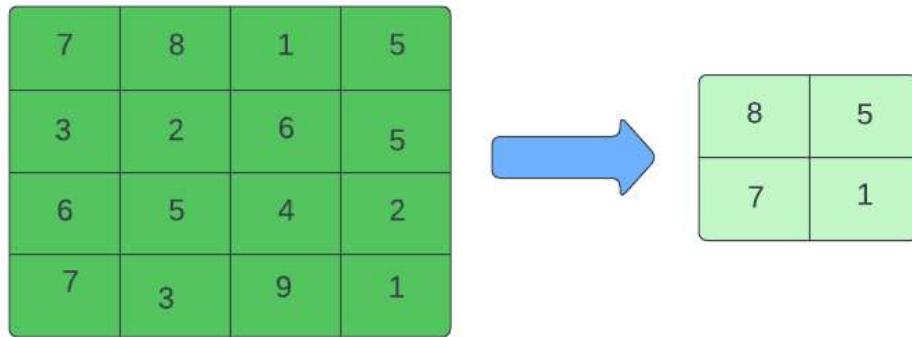


Fig 3: Max Pooling Layer

Before we get to the fully connected layer, a re lu correction layer uses the rectified linear unit in every convolution layer and to prevent overfitting is also observed in this layer.

Fully Connected Layer

This layer is the neural network layer and it is always at the end where information is taken from the previous layer and lays it out flat. After, it looks at the flat information and tries to figure out the chances of each possible outcome or class. I used the linear combination and the activation function to create a new output vector thus, n-dimensional vector, where the N denotes the number of classes of our image classification.

Fig 4: Input-Output Neuron

Secondary Data

For this machine learning model, I used the public plant village dataset and I included other dataset which were not part such as cocoa.

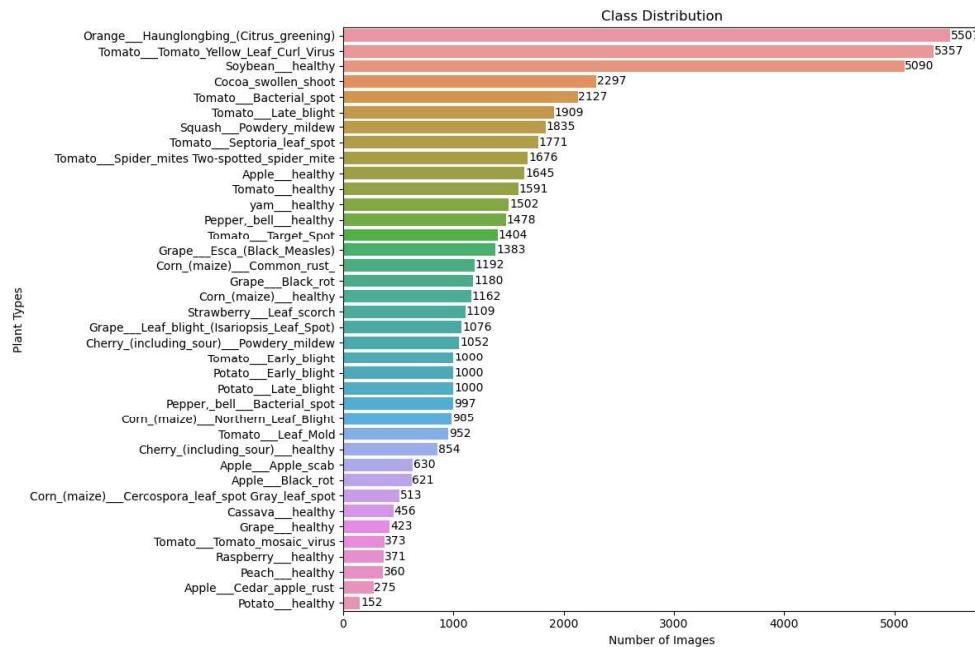
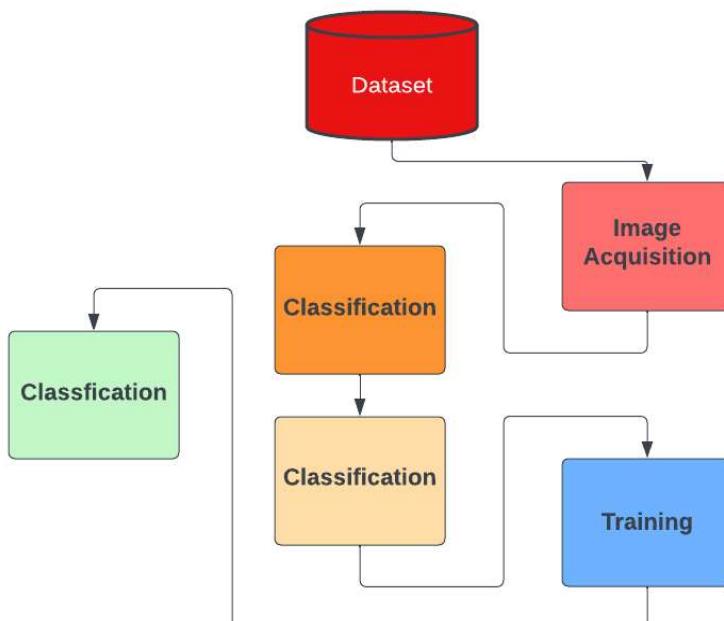


Fig 5 : Graph of Number of Images vs Plant Types

The processed dataset of images was trained based on the training model:



From Figure 5, after the image is acquired it goes through the classification process where the feature extraction uses the convolutional and pooling layers. This is where plants are classified whether it is infected with disease or it is healthy.

Preparing and Training and Testing Data

I split the **[1]** data into training and test sets with 80% training and 20% testing, Then training and validation sets were splitted into 80% training and 20% validation.

Data Preprocessing: Figure 6 shows the preprocessing code for the CNN model

```
batch_size = 40
train_datagen = ImageDataGenerator(
    rescale=1./255,
    rotation_range=20,
    width_shift_range=0.2,
    height_shift_range=0.2,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True
)

train_generator = train_datagen.flow_from_dataframe(
    train_df,
    x_col='image_path',
    y_col='label',
    target_size=(224, 224),
    batch_size=batch_size,
    class_mode='categorical'
)

val_datagen = ImageDataGenerator(rescale=1./255)

val_generator = val_datagen.flow_from_dataframe(
    val_df,
    x_col='image_path',
    y_col='label',
    target_size=(224, 224),
    batch_size=batch_size,
    class_mode='categorical'
)

test_datagen = ImageDataGenerator(rescale=1./255)
```

Data preprocessing with a defined batch size

Data augmentation for training set, rescaling pixel values, randomly rotate images up to 20 degrees

Creating a data generator for the training set, training data frame, column containing image file paths and labels, resize images to pixels

Data augmentation for the validation set

Creating a data generator for the test set

 Number: 1

Author: Lauretta Shardow

Date: 12/09/2023 12:08:38 pm

data collected from secondary source?

This section of the model defines the data generators for the training, validation and test sets. These data generators perform data augmentation for the training set and rescaling for all sets. They also specify the target image size and batch size.

Model Selection: After specifying the target image size and batch size, MobileNetV2 architecture is used as the base model with pre-trained ImageNet weights and removes the top fully connected layer.

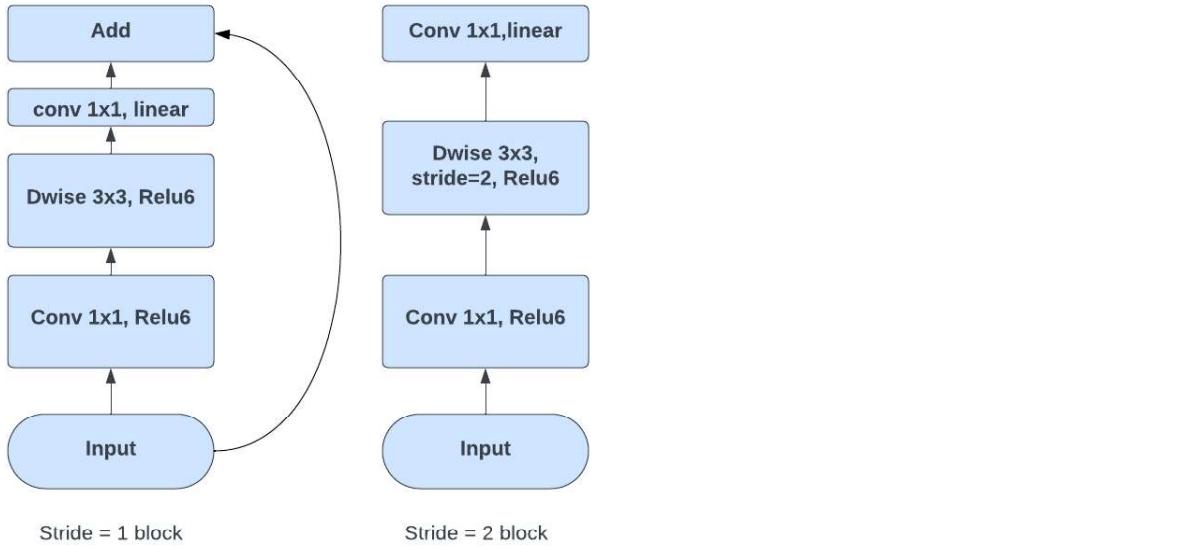


Figure 7: MobileNetV2

With **MobileNetV2**, there are two types of blocks namely stride 1 block and stride 2 block which has the first layer as 1x1 convolution with RELU6. The next layer consists of the depthwise convolution and the last layer is another 1x1 convolution without non-linearity.

Input	Operator	Output
$r \times n \times t$	$1 \times 1 \text{ conv2d, ReLU6}$	$r \times w \times (kt)$
$r \times n \times kt$	$3 \times 3 \text{ dwise } s=s, \text{ReLU6}$	$\frac{r}{s} \times \frac{n}{s} \times (kt)$
$\frac{r}{s} \times \frac{n}{s} \times kt$	$\text{Linear } 1 \times 1 \text{ conv2d}$	$\frac{r}{s} \times \frac{n}{s} \times t'$

When there is an expansion factor of k where k = 6 for all experiments, If the input is 32 channels, the internal output would be $32 \times k = 32 \times 6 = 192$ channels.

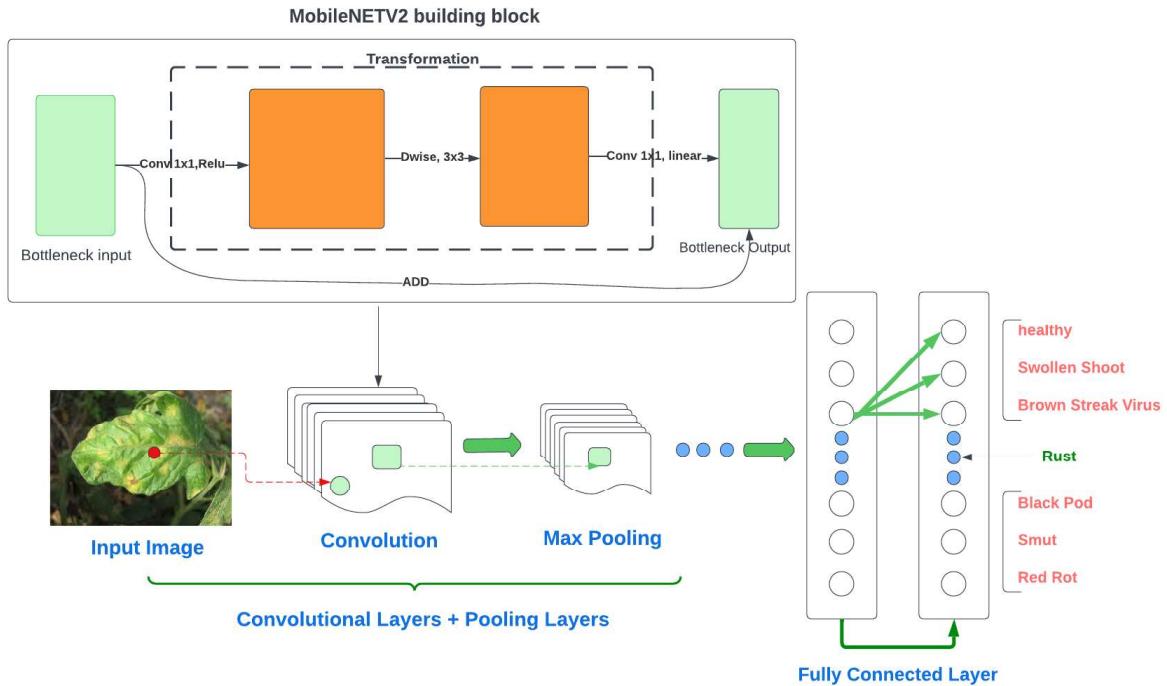


Figure 8: Image showing the MobileNETV2 building block at the convolutional layer

Model Building and Training:

Figure 9 : Image showing the code for model building and training using adam optimizer, softmax and epochs

```
# Step 5: Model Building
x = base_model.output
x = GlobalAveragePooling2D()(x)
x = Dense(1024, activation='relu')(x)
predictions = Dense(num_classes, activation='softmax')(x)
model = Model(inputs=base_model.input, outputs=predictions)

# Step 6: Model Training
learning_rate = 0.001
model.compile(optimizer=Adam(learning_rate),
              loss='categorical_crossentropy',
              metrics=['accuracy'])

epochs = 10
history = model.fit(train_generator, epochs=epochs, validation_data=val_generator)
```

Building the classification head on top of the base model

Compiling the model with Adam optimizer

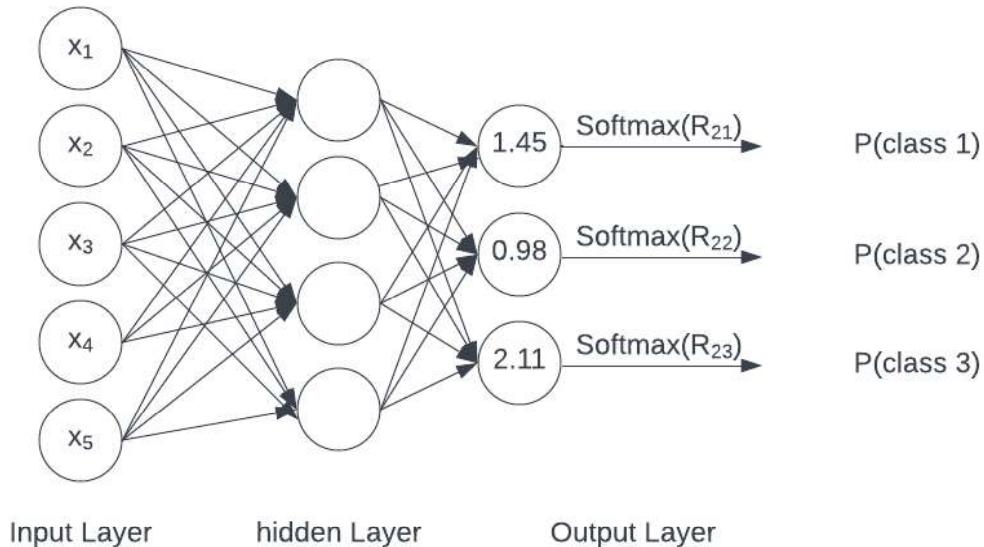
the final model by combining the base model and the custom classification head

Figure 9 shows how it constructs a custom classification head on top of the base model, consisting of global average pooling, a fully connected layer with ReLU activation, and an

output layer with softmax activation. The softmax activation function uses values of R21, R22, R23 to determine the final probability value. Here is the equation for the softMac activation function:

$$\text{softmax}(R_i) = \frac{\exp(R_i)}{\sum_j \exp(R_j)}$$

R: The R represents the values from the neurons of the output layer. To normalize and convert them into probabilities, we find the quotient between the R values and the sum of exponential values.



Evaluation Metrics

To ensure that the application operates at a maximum efficiency, fine-tuning all parameters to achieve accuracy is the most suitable way. Hence I use the loss function called the cross entropy function. This function helps to indicate the amount of uncertainty in machine learning events. The cross entropy is given by the equation:

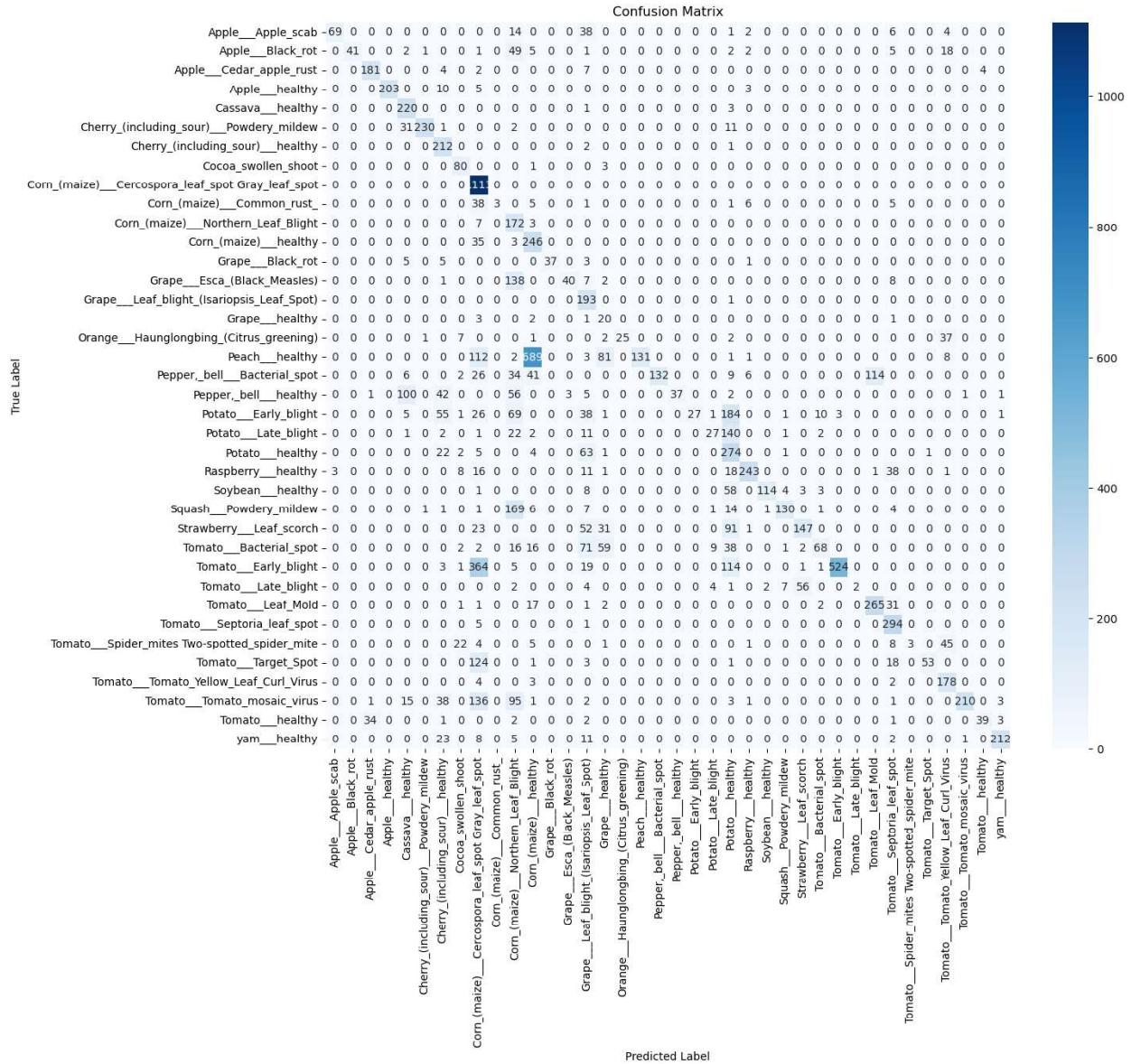
$$H(t, p) = - \sum_{s \in S} t(s) \cdot \log(p(s))$$

t(s) : the true probability distribution (one-shot)

q(x) : The model's predicted probability distribution

Confusion Matrix.

Figure 11



A confusion matrix of the CNN trained on 80% of images of the dataset and tested on 20% of the remaining images for model accuracy. Figure 11 shows the confusion matrix generated as a result of my machine learning model. The rows represent the actual classes of image and the columns represent the CNN's class prediction. Each cell in the matrix represents the percentage of images of the row's class that were classified to the column's class. It displays the number of

correct predictions: true positives and true negatives and the accuracy of the model can be calculated. When the diagonal of the matrix is higher than its surrounding then it has a higher accuracy and from the diagram, we could see that the highest numbers from Apple_Apple Scab (69) to yam_health (212) creates a linear diagonal. Using the Accuracy equation and precision equation of CNN evaluation :

$$\text{Accuracy} = \frac{\text{TRUE PREDICTIONS}}{\text{ALL PREDICTIONS}} = \frac{(TP + TN)}{TP + TN + FP + FN}$$

$$\text{Precision} = \frac{\text{Actual Spam}}{\text{Predicted Spam}} = \frac{TP}{TP+FP}$$

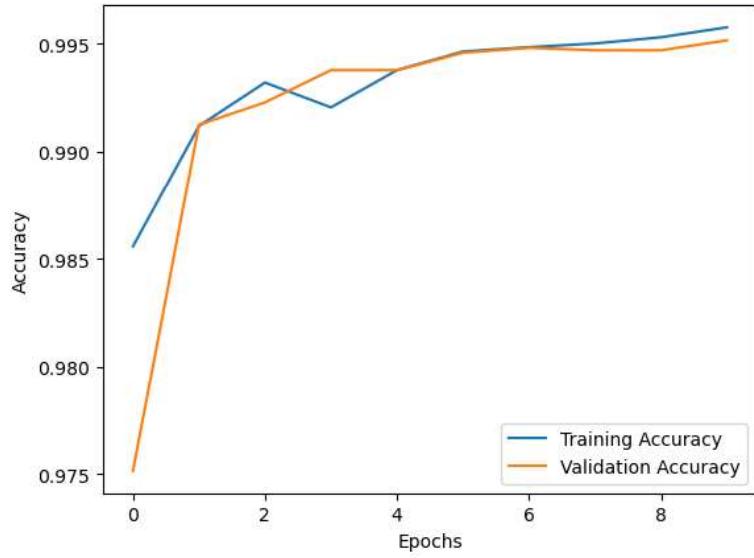
Where: TP = True positive, TN = True negative, FP = False positive, FN = False negative

Using python computation, I generated the accuracy of each plant image and below is the results:

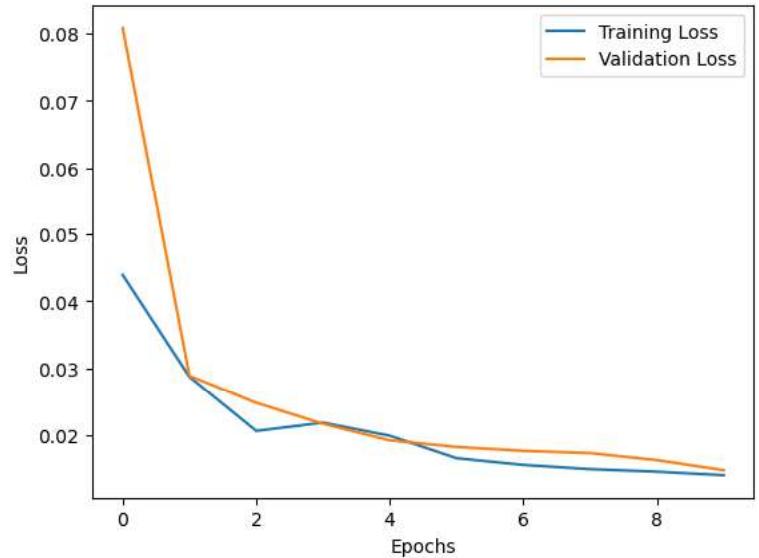
```
# Confusion Matrix and Classification Report
plt.figure(figsize=(14, 12))
conf_matrix = confusion_matrix(test_true_labels, test_predicted_labels)
class_names = list(class_labels_dict.keys())
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=class_names, yticklabels=class_names)
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Confusion Matrix')
plt.show();

print(classification_report(test_true_labels, test_predicted_labels, target_names=class_names))
```

	precision	recall	f1-score	support
Apple__Apple_scab	0.96	0.51	0.67	134
Apple__Black_rot	1.00	0.32	0.49	127
Apple__Cedar_apple_rust	0.83	0.91	0.87	198
Apple__healthy	1.00	0.92	0.96	221
Cassava__healthy	0.57	0.98	0.72	224
Cherry_(including_sour)__Powdery_mildew	0.99	0.84	0.91	275
Cherry_(including_sour)__healthy	0.50	0.99	0.67	215
Cocoa_swollen_shoot	0.63	0.95	0.76	84
Corn_(maize)__Cercospora_leaf_spot_Gray_leaf_spot	0.54	1.00	0.70	1113
Corn_(maize)__Common_rust	1.00	0.05	0.10	59
Corn_(maize)__Northern_Leaf_Blight	0.20	0.95	0.33	182
Corn_(maize)__healthy	0.23	0.87	0.37	284
Grape__Black_rot	1.00	0.73	0.84	51
Grape__Esca_(Black_Measles)	0.93	0.20	0.33	196
Grape__Leaf_blight_(Isariopsis_Leaf_Spot)	0.34	0.99	0.51	194
Grape__healthy	0.10	0.74	0.17	27
Orange__Haunglongbing_(citrus_greening)	1.00	0.33	0.50	75
Peach__healthy	1.00	0.13	0.23	1028
Pepper,_bell__Bacterial_spot	1.00	0.36	0.53	370
Pepper,_bell__healthy	1.00	0.15	0.26	248
Potato__Early_blight	1.00	0.06	0.12	422
Potato__Late_blight	0.64	0.13	0.22	209
Potato__healthy	0.28	0.73	0.41	373
Raspberry__healthy	0.91	0.71	0.80	340
Soybean__healthy	0.97	0.60	0.74	191
Squash__Powdery_mildew	0.90	0.39	0.54	336
Strawberry__Leaf_scorch	0.70	0.43	0.53	345
Tomato__Bacterial_spot	0.78	0.24	0.37	284
Tomato__Early_blight	0.99	0.51	0.67	1032
Tomato__Late_blight	1.00	0.03	0.05	78
Tomato__Leaf_Mold	0.70	0.83	0.76	320
Tomato__Septoria_leaf_spot	0.69	0.98	0.81	300
Tomato__Spider_mites_Two-spotted_spider_mite	1.00	0.03	0.07	89
Tomato__Target_Spot	0.98	0.27	0.42	200
Tomato__Tomato_Yellow_Leaf_Curl_Virus	0.61	0.95	0.74	187
Tomato__Tomato_mosaic_virus	0.99	0.42	0.58	506
Tomato__healthy	0.91	0.48	0.62	82
vam__healthy	0.96	0.81	0.88	262



Validation Accuracy Graph



Training Loss and Epochs

1 HyperParameter Tuning

Model Testing

Economics

According to the world bank, “food security is defined when all people, at all times, have physical and economic access to sufficient safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life”.

Profit maximization

Yield production and crop analysis and predictions

Cost-Benefit Analysis: compare the cost of implementing and maintaining the technology with the benefits, such as increased crop yields and reduced losses due to diseases.

Economies of Scale: may lead to lower per-unit costs, making the technology more accessible to farmers.

Production function: discuss how it can increase agricultural output by reduce the negative impact of diseases on crop yields.

Resource allocation: help farmers allocate resources such as fertilizers, pesticides and labor more efficiently by targeting affected areas

Market structure: how it might affect competition among farmers, input suppliers

Risk Management: farmers can make informed decisions based on disease warnings

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No test yet?

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(<https://www.worldbank.org/en/topic/agriculture/brief/food-security-update/what-is-food-security>)

(International Journal of Scientific Research in Engineering and Management (IJSREM))

<https://www.analyticsvidhya.com/blog/2021/04/introduction-to-softmax-for-neural-network/> - softmax activation function

The Ministry of Food and Agriculture provides services to local farmers such as monitoring of seed and planting material production of crop species, education and training on pesticide and disease management. However these programs may not be efficient in the wide scale due to the cost involved in conducting the programs and also not all local farmers may be educated on pest and disease management. Based on the information obtained about the existing solution, I believe developing a plant disease detection model for local farmers will help mitigate loss of income which will increase food security.

Cs = 1300 words

Economics = 1000 words

Evaluation: 200 words

Introduction, methodology = 800 words

Evaluation: 200 words

Conclusion = 500 words

<https://www.v7labs.com/blog/cross-entropy-loss-guide>

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