

ninjacart-cv-image-classification

March 26, 2024

[]: NINJACART Business Case Study By RATNESH KUMAR

1 Problem Statement

- Ninjacart is India's largest fresh produce supply chain company. They are pioneers in solving one of the toughest supply chain problems of the world by leveraging innovative technology.
- They source fresh produce from farmers and deliver them to businesses within 12 hours.
- An integral component of their automation process is the development of robust classifiers which can distinguish between images of different types of vegetables, while also correctly labeling images that do not contain any one type of vegetable as noise.
- As a starting point, ninjacart has provided us with a dataset scraped from the web which contains train and test folders, each having 4 sub-folders with images of onions, potatoes, tomatoes and some market scenes.
- We have been tasked with preparing a multiclass classifier for identifying these vegetables. The dataset provided has all the required images to achieve the task.

1.1 Context

- This dataset contains images of the following food items: noise-Indian market and images of vegetables- onion, potato and tomato.

1.2 Data Collection

- The images in this dataset were scraped from Google.

1.3 Content

- This dataset contains a folder train, which has a total of 3135 images, split into four folders as follows:
 - Tomato : 789
 - Potato : 898
 - Onion : 849
 - Indian market : 599

- This dataset contains another folder test which has a total of 351 images, split into four folders
 - Tomato : 106
 - potato : 83
 - onion : 81
 - Indian market : 81

1.4 Objective :

- The objective is to develop a program that can recognize the vegetable item(s) in a photo and identify them for the user.

1.4.1 Concepts Tested:

- Dataset Preparation & Visualization
- CNN models
- Implementing Callbacks
- Deal with Overfitting
- Transfer Learning

[]:

2 Downloading Data

[]: `!gdown 1c1ZX-1V_MLxKHSyeyTheX50CQtNCUcqT`

Downloading...

From: https://drive.google.com/uc?id=1c1ZX-1V_MLxKHSyeyTheX50CQtNCUcqT

To: /content/ninjacart_data.zip

100% 275M/275M [00:03<00:00, 80.2MB/s]

[]:

3 unzip

[]: `%%time`

`!unzip -q /content/ninjacart_data.zip`

CPU times: user 16.4 ms, sys: 7.5 ms, total: 23.9 ms

Wall time: 2.22 s

```
[ ]:
```

```
# Importing common libraries
```

```
[ ]: %%time
```

```
import os
import glob
import random
import numpy as np
import pandas as pd
import sklearn.metrics as metrics
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

# Import tensorflow and its modules
import tensorflow as tf
from tensorflow import keras # this allows <keras.> instead of <tf.keras.>
from tensorflow.keras import layers # this allows <layers.> instead of <tf.
    ↳keras.layers.>
tf.keras.utils.set_random_seed(111) # set random seed

# To suppress any warnings during the flow
import warnings
warnings.filterwarnings('ignore')
```

```
CPU times: user 2.8 s, sys: 419 ms, total: 3.22 s
```

```
Wall time: 3.81 s
```

```
[ ]:
```

```
[ ]:
```

```
[ ]:
```

```
[ ]:
```

4 train data distribution

```
[ ]: # train data distribution
```

```
[ ]: %%time
```

```
class_dirs_train = os.listdir("ninjacart_data/train") # list all directories_
    ↳inside "train" folder
```

```

image_dict_train = {} # dict to store image array(key) for every class(value)
count_dict_train = {} # dict to store count of files(key) for every class(value)

for _ in range(5):
    # iterate over all class_dirs
    for cls in class_dirs_train:
        # get list of all paths inside the subdirectory
        file_paths = glob.glob(f'ninjacart_data/train/{cls}/*')
        # count number of files in each class and add it to count_dict_train
        count_dict_train[cls] = len(file_paths)
        # select random item from list of image paths
        image_path = random.choice(file_paths)
        # load image using keras utility function and save it in image_dict_train
        image_dict_train[cls] = tf.keras.utils.load_img(image_path)

    ## Viz Random Sample from each class

plt.figure(figsize=(15, 12))
# iterate over dictionary items (class label, image array)
for i, (cls,img) in enumerate(image_dict_train.items()):
    # create a subplot axis
    ax = plt.subplot(3, 4, i + 1)
    # plot each image
    plt.imshow(img)
    # set "class name" along with "image size" as title
    plt.title(f'{cls}, {img.size}')
    plt.axis("off")

plt.show()

## Let's now Plot the Data Distribution of Training Data across Classes
df_count_train = pd.DataFrame({
    "class": count_dict_train.keys(),      # keys of count_dict are class labels
    "count": count_dict_train.values(),    # value of count_dict contain counts
    # of each class
})

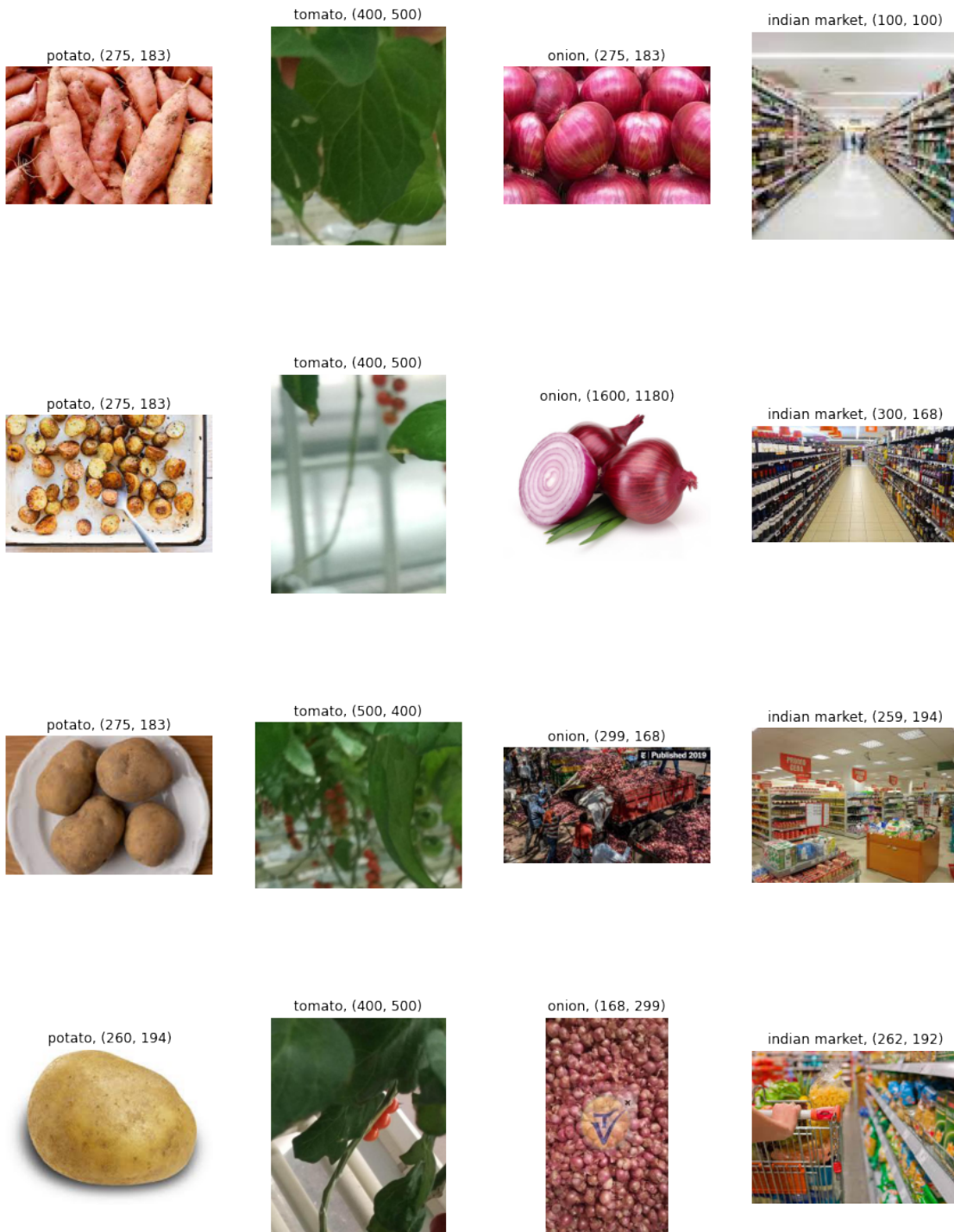
print()
print()
print()

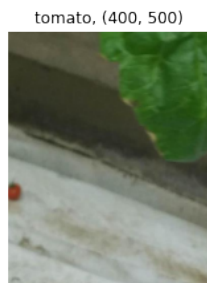
print("Count of training samples per class:\n", df_count_train)

print()
print()
print()

```

```
# draw a bar plot using pandas in-built plotting function
df_count_train.plot.bar(x='class', y='count', title="Training Data Count per_
↪class")
```





Count of training samples per class:

	class	count
0	potato	898
1	tomato	789
2	onion	849
3	indian market	599

CPU times: user 2.95 s, sys: 392 ms, total: 3.34 s

Wall time: 3.49 s

```
[ ]: <Axes: title={'center': 'Training Data Count per class'}, xlabel='class'>
```



```
[ ]: # test data distribution
```

5 test data distribution

```
[ ]: %%time

class_dirs_test = os.listdir("ninjacart_data/test") # list all directories
↳ inside "train" folder
image_dict_test = {} # dict to store image array(key) for every class(value)
count_dict_test = {} # dict to store count of files(key) for every class(value)

for _ in range(5):
    # iterate over all class_dirs_test
    for cls in class_dirs_test:
        # get list of all paths inside the subdirectory
        file_paths = glob.glob(f'ninjacart_data/test/{cls}/*')
        # count number of files in each class and add it to count_dict_test
```

```

count_dict_test[cls] = len(file_paths)
# select random item from list of image paths
image_path = random.choice(file_paths)
# load image using keras utility function and save it in image_dict
image_dict_test[cls] = tf.keras.utils.load_img(image_path)

## Viz Random Sample from each class

plt.figure(figsize=(15, 12))
# iterate over dictionary items (class label, image array)
for i, (cls,img) in enumerate(image_dict_test.items()):
    # create a subplot axis
    ax = plt.subplot(3, 4, i + 1)
    # plot each image
    plt.imshow(img)
    # set "class name" along with "image size" as title
    plt.title(f'{cls}, {img.size}')
    plt.axis("off")

plt.show()

## Let's now Plot the Data Distribution of testing Data across Classes
df_count_test = pd.DataFrame({
    "class": count_dict_test.keys(),      # keys of count_dict are class labels
    "count": count_dict_test.values(),    # value of count_dict contain counts_
    ↪of each class
})

print()
print()
print()
print("Count of test samples per class:\n", df_count_test)

print()
print()
print()

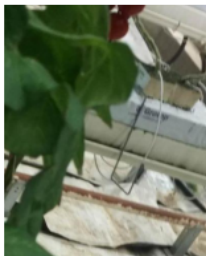
# draw a bar plot using pandas in-built plotting function
df_count_test.plot.bar(x='class', y='count', title="test Data Count per class")

```

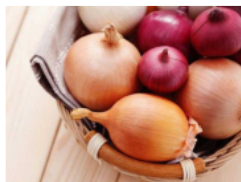

potato, (100, 100)



tomato, (400, 500)



onion, (640, 480)



indian market, (275, 183)



potato, (242, 209)



tomato, (500, 400)



onion, (640, 426)



indian market, (301, 167)



potato, (275, 183)



tomato, (500, 400)



onion, (1024, 415)



indian market, (194, 259)



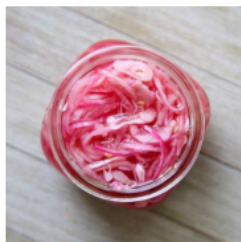
potato, (275, 183)



tomato, (400, 500)

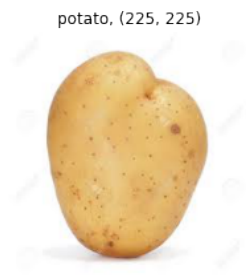


onion, (640, 640)



indian market, (297, 170)





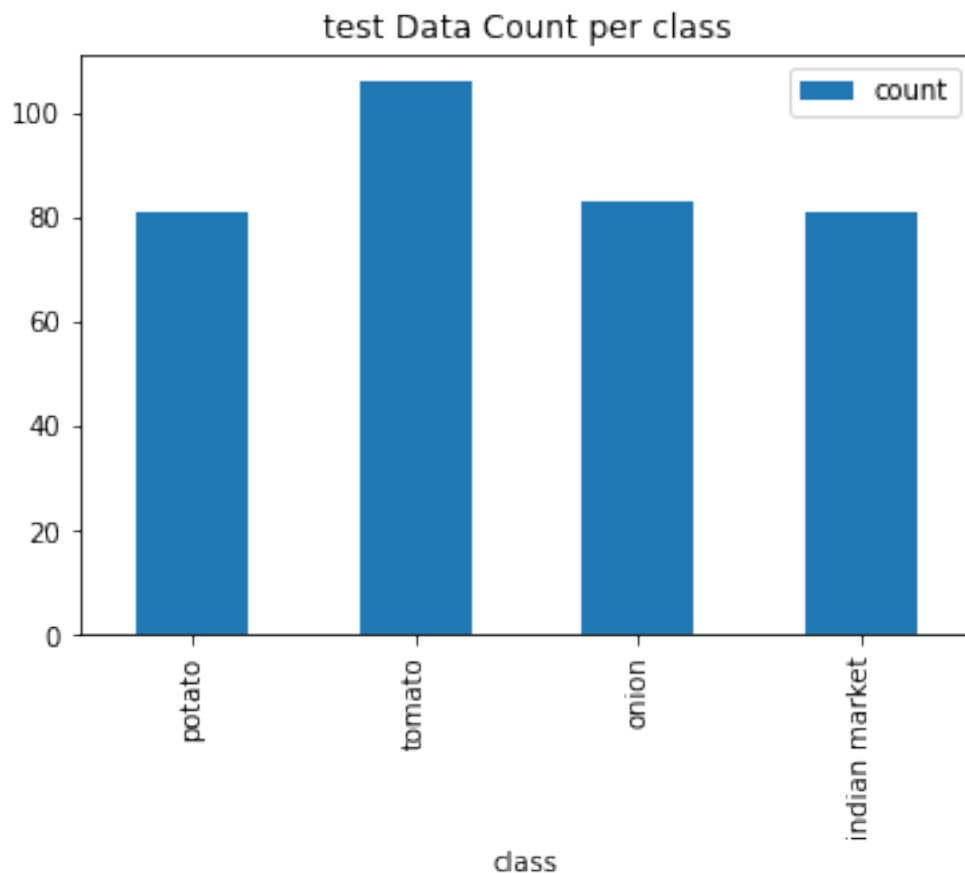
Count of test samples per class:

	class	count
0	potato	81
1	tomato	106
2	onion	83
3	indian market	81

CPU times: user 2.66 s, sys: 272 ms, total: 2.93 s

Wall time: 4.27 s

```
[ ]: <Axes: title={'center': 'test Data Count per class'}, xlabel='class'>
```



```
[ ]:
```

```
[ ]:
```

6 Loading, Resizing the data into TensorFlow

```
[ ]:
```

```
[ ]: import tensorflow as tf
import os
from sklearn.model_selection import train_test_split
```

```
[ ]: train_dir = '/content/ninjacart_data/train'
test_dir = '/content/ninjacart_data/test'

train_filenames = tf.io.gfile.glob(train_dir + '/*/*')
test_filenames = tf.io.gfile.glob(test_dir + '/*/*')
```

```
train_labels = [os.path.basename(os.path.dirname(filename)) for filename in
    ↪train_filenames]
test_labels = [os.path.basename(os.path.dirname(filename)) for filename in
    ↪test_filenames]
```

```
[ ]: np.unique(np.array(test_labels))
```

```
[ ]: array(['indian market', 'onion', 'potato', 'tomato'], dtype='<U13')
```

```
[ ]: train_filenames, val_filenames, train_labels, val_labels =
    ↪train_test_split(train_filenames, train_labels, test_size=0.2)
```

```
[ ]: data_dir = '/content/ninjacart_data/train'
img_size = (128, 128) # set the desired image size for your model
```

```
[ ]: from tensorflow.keras.preprocessing.image import ImageDataGenerator

train_data_gen = ImageDataGenerator(
    rescale=1./255, # normalize pixel values
    validation_split=0.2 # set the validation split to 20%
)

train_data = train_data_gen.flow_from_directory(
    data_dir,
    target_size=img_size,
    batch_size=32, # set the batch size for training data
    class_mode='categorical',
    subset='training'
)

val_data = train_data_gen.flow_from_directory(
    data_dir,
    target_size=img_size,
    batch_size=32, # set the batch size for validation data
    class_mode='categorical',
    subset='validation'
)
```

Found 2511 images belonging to 4 classes.

Found 624 images belonging to 4 classes.

```
[ ]: data_gen = ImageDataGenerator(
    rescale=1./255, # normalize pixel values
)
```

```
test_data = data_gen.flow_from_directory(
    test_dir,
    target_size=img_size,
    class_mode='categorical',
    shuffle=False # don't shuffle the data
)
```

Found 351 images belonging to 4 classes.

```
[ ]: height, width = img_size
height, width
```

```
[ ]: (128, 128)
```

```
[ ]:
```

```
[ ]: # Creating base ANN model :
```

7 ANN model :

```
[ ]: num_classes = 4
hidden_size_1 = 256
hidden_size_2 = 256

model = keras.Sequential(
    name="model_ANN",
    layers=[

        layers.Flatten(input_shape=(height, width, 3)),

        layers.Dense(units=hidden_size_1, activation='relu'), # hidden layer 1
        layers.Dense(units=hidden_size_2, activation='relu'), # hidden layer 2

        layers.Dense(units=num_classes, activation='softmax'), # output layer
    ]
)

model.summary()
```

Model: "model_ANN"

Layer (type)	Output Shape	Param #
--------------	--------------	---------

```

=====
flatten (Flatten)          (None, 49152)          0

dense (Dense)              (None, 256)           12583168

dense_1 (Dense)            (None, 256)           65792

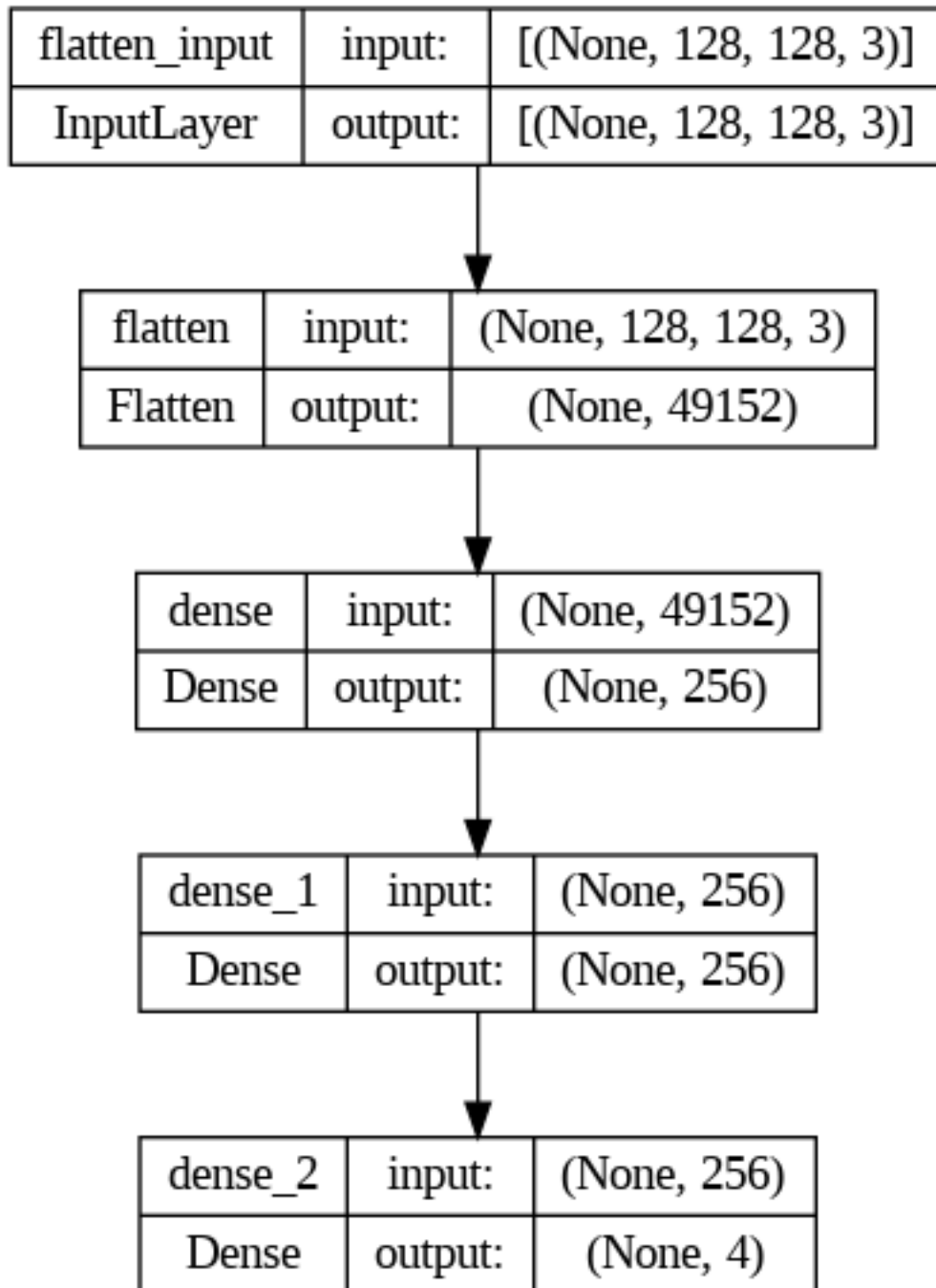
dense_2 (Dense)            (None, 4)              1028

=====
Total params: 12,649,988
Trainable params: 12,649,988
Non-trainable params: 0
-----

```

```
[ ]: tf.keras.utils.plot_model(model, to_file="model_ANN.png", show_shapes=True)
```

```
[ ]:
```



```
[ ]: model.compile(optimizer='adam',
                  loss='categorical_crossentropy',
                  metrics=['accuracy'])
```

```
[ ]: epochs = 15
     model_fit = model.fit(train_data,
```

```

        steps_per_epoch=train_data.samples//train_data.
↪batch_size, # set the steps per epoch
        validation_data=val_data,
        validation_steps=val_data.samples//val_data.batch_size, #
↪set the validation steps
        epochs=epochs)

```

Epoch 1/15

78/78 [=====] - 19s 222ms/step - loss: 7.4552 - accuracy: 0.3897 - val_loss: 1.2296 - val_accuracy: 0.5329

Epoch 2/15

78/78 [=====] - 18s 229ms/step - loss: 1.0211 - accuracy: 0.6370 - val_loss: 1.0521 - val_accuracy: 0.5789

Epoch 3/15

78/78 [=====] - 22s 284ms/step - loss: 0.9280 - accuracy: 0.6478 - val_loss: 1.1942 - val_accuracy: 0.6036

Epoch 4/15

78/78 [=====] - 25s 322ms/step - loss: 0.8190 - accuracy: 0.6914 - val_loss: 0.8565 - val_accuracy: 0.6875

Epoch 5/15

78/78 [=====] - 20s 253ms/step - loss: 0.7475 - accuracy: 0.7168 - val_loss: 0.9300 - val_accuracy: 0.6250

Epoch 6/15

78/78 [=====] - 25s 316ms/step - loss: 0.7467 - accuracy: 0.7039 - val_loss: 1.0266 - val_accuracy: 0.6086

Epoch 7/15

78/78 [=====] - 17s 217ms/step - loss: 0.7729 - accuracy: 0.6846 - val_loss: 1.1354 - val_accuracy: 0.5740

Epoch 8/15

78/78 [=====] - 19s 246ms/step - loss: 0.7782 - accuracy: 0.6942 - val_loss: 1.1281 - val_accuracy: 0.5806

Epoch 9/15

78/78 [=====] - 15s 190ms/step - loss: 0.6321 - accuracy: 0.7487 - val_loss: 1.1061 - val_accuracy: 0.5938

Epoch 10/15

78/78 [=====] - 15s 197ms/step - loss: 0.6027 - accuracy: 0.7672 - val_loss: 1.0798 - val_accuracy: 0.6299

Epoch 11/15

78/78 [=====] - 18s 233ms/step - loss: 0.6081 - accuracy: 0.7580 - val_loss: 1.2227 - val_accuracy: 0.6118

Epoch 12/15

78/78 [=====] - 17s 223ms/step - loss: 0.6606 - accuracy: 0.7443 - val_loss: 0.9007 - val_accuracy: 0.6711

Epoch 13/15

78/78 [=====] - 16s 210ms/step - loss: 0.5919 - accuracy: 0.7769 - val_loss: 1.4941 - val_accuracy: 0.5214

Epoch 14/15


```

78/78 [=====] - 14s 185ms/step - loss: 0.6072 -
accuracy: 0.7616 - val_loss: 0.9394 - val_accuracy: 0.6595
Epoch 15/15
78/78 [=====] - 16s 212ms/step - loss: 0.4816 -
accuracy: 0.8161 - val_loss: 0.9144 - val_accuracy: 0.6842

```

```

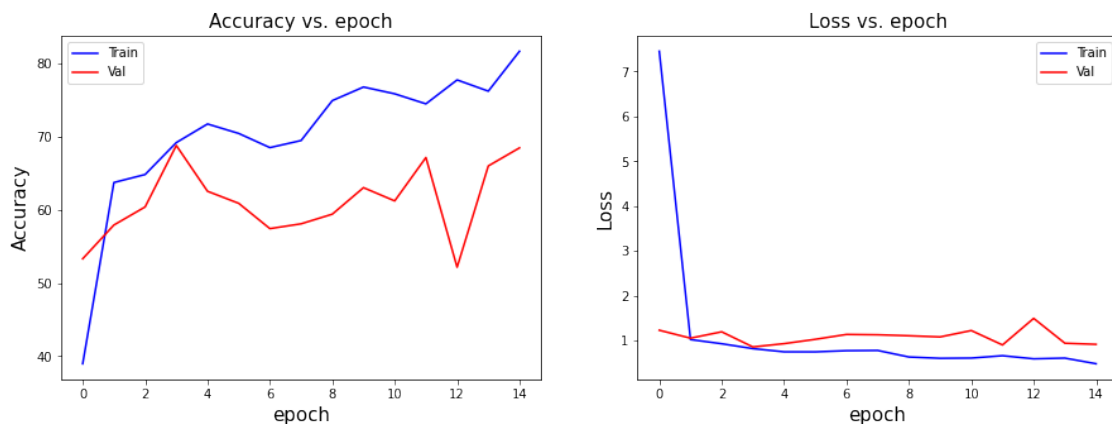
[ ]: fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(15,5))
    ax = axes.ravel()

    #accuracy graph
    ax[0].plot(range(0,model_fit.params['epochs']), [acc * 100 for acc in model_fit.
        ↳history['accuracy']], label='Train', color='b')
    ax[0].plot(range(0,model_fit.params['epochs']), [acc * 100 for acc in model_fit.
        ↳history['val_accuracy']], label='Val', color='r')
    ax[0].set_title('Accuracy vs. epoch', fontsize=15)
    ax[0].set_ylabel('Accuracy', fontsize=15)
    ax[0].set_xlabel('epoch', fontsize=15)
    ax[0].legend()

    #loss graph
    ax[1].plot(range(0,model_fit.params['epochs']), model_fit.history['loss'],
        ↳label='Train', color='b')
    ax[1].plot(range(0,model_fit.params['epochs']), model_fit.history['val_loss'],
        ↳label='Val', color='r')
    ax[1].set_title('Loss vs. epoch', fontsize=15)
    ax[1].set_ylabel('Loss', fontsize=15)
    ax[1].set_xlabel('epoch', fontsize=15)
    ax[1].legend()

    #display the graph
    plt.show()

```



```

[ ]: test_loss, test_acc = model.evaluate(test_data)

print('Test accuracy:', test_acc)

print()
print()

y_true = test_data.labels
y_pred = np.argmax(model.predict(test_data), axis=-1)

from sklearn.metrics import classification_report, confusion_matrix

cm = confusion_matrix(y_true, y_pred)

print('Confusion matrix:')
print(cm)

# Print the classification report
class_names = list(train_data.class_indices.keys())
report = classification_report(y_true, y_pred, target_names=class_names)
print('Classification report:')
print(report)

print()
print()
print()
print()

# Plot confusion matrix
plt.matshow(cm)
plt.title('Confusion matrix')
plt.colorbar()
plt.xlabel('Predicted label')
plt.ylabel('True label')
plt.xticks(np.arange(len(class_names)), class_names, rotation=45)
plt.yticks(np.arange(len(class_names)), class_names)

# Add text annotations to confusion matrix
for i in range(cm.shape[0]):
    for j in range(cm.shape[1]):
        plt.text(j, i, cm[i, j], ha='center', va='center', color='white')

```

```
plt.show()
```

```
11/11 [=====] - 2s 153ms/step - loss: 1.0572 -  
accuracy: 0.6154  
Test accuracy: 0.6153846383094788
```

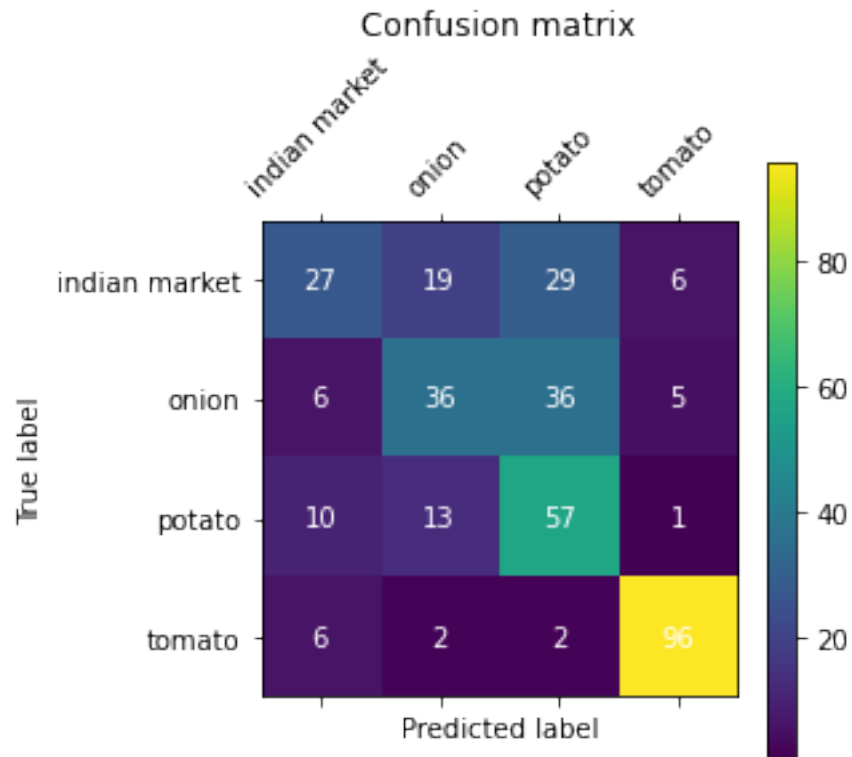
```
11/11 [=====] - 2s 151ms/step
```

Confusion matrix:

```
[[27 19 29  6]  
 [ 6 36 36  5]  
 [10 13 57  1]  
 [ 6  2  2 96]]
```

Classification report:

	precision	recall	f1-score	support
indian market	0.55	0.33	0.42	81
onion	0.51	0.43	0.47	83
potato	0.46	0.70	0.56	81
tomato	0.89	0.91	0.90	106
accuracy			0.62	351
macro avg	0.60	0.59	0.58	351
weighted avg	0.62	0.62	0.61	351



[]:

[]:

[]:

8 CNN

8.1 CNN Architecture 1:

```
[ ]: from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense

model = Sequential(

    name="model_CNN",
    layers = [

        Conv2D(filters = 32,
                kernel_size = (3, 3),
                activation='relu',
```

```

        padding="same" ,
        input_shape=(128, 128, 3)),
MaxPooling2D((2, 2)),

Conv2D(64,
      (3, 3),
      padding="same" ,
      activation='relu'),
MaxPooling2D((2, 2)),

Conv2D(128,
      (3, 3),
      padding="same",
      activation='relu'),
MaxPooling2D((2, 2)),

Flatten(),

Dense(128, activation='relu'),
Dense(4, activation='softmax')
])

```

```
[ ]: tf.keras.utils.plot_model(model, to_file="model_CNN.png", show_shapes=True)
```

```
[ ]:
```

conv2d_9_input	input:	[(None, 128, 128, 3)]
InputLayer	output:	[(None, 128, 128, 3)]



conv2d_9	input:	(None, 128, 128, 3)
Conv2D	output:	(None, 128, 128, 32)



max_pooling2d_9	input:	(None, 128, 128, 32)
MaxPooling2D	output:	(None, 64, 64, 32)



conv2d_10	input:	(None, 64, 64, 32)
Conv2D	output:	(None, 64, 64, 64)



max_pooling2d_10	input:	(None, 64, 64, 64)
MaxPooling2D	output:	(None, 32, 32, 64)



conv2d_11	input:	(None, 32, 32, 64)
Conv2D	output:	(None, 32, 32, 128)



max_pooling2d_11	input:	(None, 32, 32, 128)
MaxPooling2D	output:	(None, 16, 16, 128)



flatten_4	input:	(None, 16, 16, 128)
Flatten	output:	(None, 32768)



dense_9	input:	(None, 32768)
Dense	output:	(None, 128)



dense_10	input:	(None, 128)
Dense	output:	(None, 4)

```
[ ]: model.summary()
```

```
Model: "model_CNN"
```

Layer (type)	Output Shape	Param #
conv2d_6 (Conv2D)	(None, 128, 128, 32)	896
max_pooling2d_6 (MaxPooling 2D)	(None, 64, 64, 32)	0
conv2d_7 (Conv2D)	(None, 64, 64, 64)	18496
max_pooling2d_7 (MaxPooling 2D)	(None, 32, 32, 64)	0
conv2d_8 (Conv2D)	(None, 32, 32, 128)	73856
max_pooling2d_8 (MaxPooling 2D)	(None, 16, 16, 128)	0
flatten_3 (Flatten)	(None, 32768)	0
dense_7 (Dense)	(None, 128)	4194432
dense_8 (Dense)	(None, 4)	516
Total params: 4,288,196		
Trainable params: 4,288,196		
Non-trainable params: 0		

```
[ ]: model.compile(  
    optimizer='adam',  
    loss='categorical_crossentropy',  
    metrics=['accuracy']  
)
```

```
[ ]: model_fit = model.fit(  
    train_data,  
    steps_per_epoch=train_data.samples//train_data.batch_size, # set the steps_  
    ↪per epoch  
    validation_data=val_data,
```

```

        validation_steps=val_data.samples//val_data.batch_size, # set the
↪validation steps
        epochs=10 # set the number of epochs
    )

```

```

Epoch 1/10
78/78 [=====] - 19s 220ms/step - loss: 0.9302 -
accuracy: 0.6168 - val_loss: 0.6767 - val_accuracy: 0.7385
Epoch 2/10
78/78 [=====] - 15s 189ms/step - loss: 0.4770 -
accuracy: 0.8161 - val_loss: 0.6175 - val_accuracy: 0.7632
Epoch 3/10
78/78 [=====] - 16s 209ms/step - loss: 0.3917 -
accuracy: 0.8528 - val_loss: 0.5281 - val_accuracy: 0.7862
Epoch 4/10
78/78 [=====] - 17s 213ms/step - loss: 0.3382 -
accuracy: 0.8697 - val_loss: 0.5281 - val_accuracy: 0.8109
Epoch 5/10
78/78 [=====] - 16s 209ms/step - loss: 0.3170 -
accuracy: 0.8745 - val_loss: 0.4418 - val_accuracy: 0.8240
Epoch 6/10
78/78 [=====] - 16s 205ms/step - loss: 0.2280 -
accuracy: 0.9117 - val_loss: 0.4180 - val_accuracy: 0.8503
Epoch 7/10
78/78 [=====] - 15s 190ms/step - loss: 0.1912 -
accuracy: 0.9266 - val_loss: 0.4427 - val_accuracy: 0.8355
Epoch 8/10
78/78 [=====] - 16s 211ms/step - loss: 0.1386 -
accuracy: 0.9439 - val_loss: 0.5571 - val_accuracy: 0.8454
Epoch 9/10
78/78 [=====] - 17s 220ms/step - loss: 0.0971 -
accuracy: 0.9657 - val_loss: 0.4645 - val_accuracy: 0.8487
Epoch 10/10
78/78 [=====] - 14s 176ms/step - loss: 0.1144 -
accuracy: 0.9609 - val_loss: 0.6013 - val_accuracy: 0.8273

```

```

[ ]: test_loss, test_acc = model.evaluate(test_data)

print('Test accuracy:', test_acc)

print()
print()

y_true = test_data.labels
y_pred = np.argmax(model.predict(test_data), axis=-1)

```



```

from sklearn.metrics import classification_report, confusion_matrix

cm = confusion_matrix(y_true, y_pred)

print('Confusion matrix:')
print(cm)

# Print the classification report
class_names = list(train_data.class_indices.keys())
report = classification_report(y_true, y_pred, target_names=class_names)
print('Classification report:')
print(report)

print()
print()
print()
print()

# Plot confusion matrix
plt.matshow(cm)
plt.title('Confusion matrix')
plt.colorbar()
plt.xlabel('Predicted label')
plt.ylabel('True label')
plt.xticks(np.arange(len(class_names)), class_names, rotation=45)
plt.yticks(np.arange(len(class_names)), class_names)

# Add text annotations to confusion matrix
for i in range(cm.shape[0]):
    for j in range(cm.shape[1]):
        plt.text(j, i, cm[i, j], ha='center', va='center', color='white')

plt.show()

```

11/11 [=====] - 2s 145ms/step - loss: 0.5620 - accuracy: 0.8547

[]:

Test accuracy: 0.8547008633613586

[]:

11/11 [=====] - 2s 146ms/step

[]:

[]:

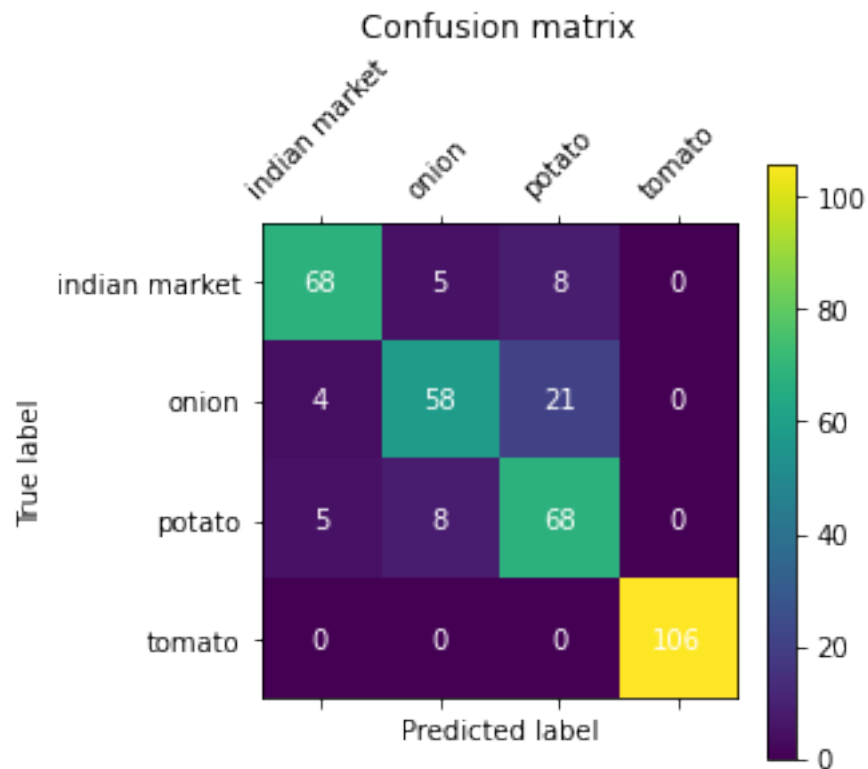
Confusion matrix:

```
[[ 68  5  8  0]
 [  4 58 21  0]
 [  5  8 68  0]
 [  0  0  0 106]]
```

Classification report:

	precision	recall	f1-score	support
indian market	0.88	0.84	0.86	81
onion	0.82	0.70	0.75	83
potato	0.70	0.84	0.76	81
tomato	1.00	1.00	1.00	106
accuracy			0.85	351
macro avg	0.85	0.84	0.84	351
weighted avg	0.86	0.85	0.86	351

[]:

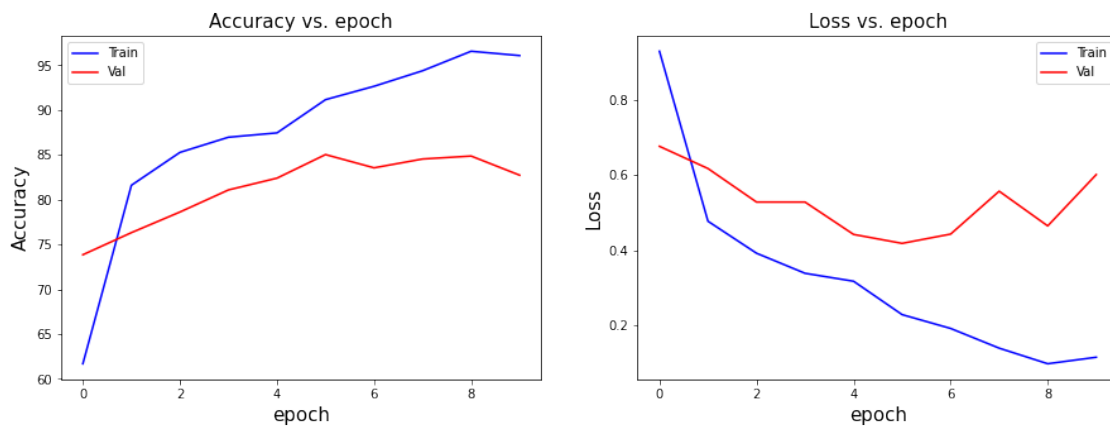


```
[ ]: fig, axes = plt.subplots(nrows=1, ncols=2,figsize=(15, 5))
ax = axes.ravel()

#accuracy graph
ax[0].plot(range(0,model_fit.params['epochs']), [acc * 100 for acc in model_fit.
    ↳history['accuracy']], label='Train', color='b')
ax[0].plot(range(0,model_fit.params['epochs']), [acc * 100 for acc in model_fit.
    ↳history['val_accuracy']], label='Val', color='r')
ax[0].set_title('Accuracy vs. epoch', fontsize=15)
ax[0].set_ylabel('Accuracy', fontsize=15)
ax[0].set_xlabel('epoch', fontsize=15)
ax[0].legend()

#loss graph
ax[1].plot(range(0,model_fit.params['epochs']), model_fit.history['loss'],
    ↳label='Train', color='b')
ax[1].plot(range(0,model_fit.params['epochs']), model_fit.history['val_loss'],
    ↳label='Val', color='r')
ax[1].set_title('Loss vs. epoch', fontsize=15)
ax[1].set_ylabel('Loss', fontsize=15)
ax[1].set_xlabel('epoch', fontsize=15)
ax[1].legend()

#display the graph
plt.show()
```



[]:

[]:

```
[ ]: import os
import numpy as np
import tensorflow as tf
tf.keras.utils.set_random_seed(111)
from tensorflow import keras
from tensorflow.keras import layers, regularizers
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn.metrics as metrics
%matplotlib inline
```

```
[ ]: # helper function to annotate maximum values in the plots
def annot_max(x,y, xytext=(0.94,0.96), ax=None, only_y=True):
    xmax = x[np.argmax(y)]
    ymax = max(y)
    if only_y:
        text = "{:.2f}%".format(ymax)
    else:
        text= "x={:.2f}, y={:.2f}%".format(xmax, ymax)
    if not ax:
        ax=plt.gca()
    bbox_props = dict(boxstyle="square,pad=0.3", fc="w", ec="k", lw=0.72)
    arrowprops=dict(arrowstyle="->",connectionstyle="angle,angleA=0,angleB=60")
    kw = dict(xycoords='data',textcoords="axes fraction",
              arrowprops=arrowprops, bbox=bbox_props, ha="right", va="top")
    ax.annotate(text, xy=(xmax, ymax), xytext=xytext, **kw)

def plot_accuracy(model_fit):
    #accuracy graph
    x = range(0,len(model_fit.history['accuracy']))
    y_train = [acc * 100 for acc in model_fit.history['accuracy']]
    y_val = [acc * 100 for acc in model_fit.history['val_accuracy']]

    plt.plot(x, y_train, label='Train', color='b')
    annot_max(x, y_train, xytext=(0.7,0.9))
    plt.plot(x, y_val, label='Val', color='r')
    annot_max(x, y_val, xytext=(0.8,0.7))
    plt.ylabel('Accuracy', fontsize=15)
    plt.xlabel('epoch', fontsize=15)
    plt.legend()
    plt.show()
```

```
[ ]:
```

8.2 CNN architecture 2:

```
[ ]: def architecture_2(height=128, width=128,num_classes=4):
    hidden_size = 256

    model = keras.Sequential(
        name="model_cnn_3",
        layers=[
            layers.Conv2D(filters=16,
                           kernel_size=3,
                           padding="same",
                           input_shape=(height, width, 3),
                           kernel_regularizer=regularizers.l2(1e-3)),
            layers.Activation("relu"),
            layers.BatchNormalization(),
            layers.MaxPooling2D(),
            layers.Conv2D(filters=32, kernel_size=3, padding="same",
                           kernel_regularizer=regularizers.l2(1e-3)),
            layers.Activation("relu"),
            layers.BatchNormalization(),
            layers.MaxPooling2D(),
            layers.Conv2D(filters=64, kernel_size=3, padding="same",
                           kernel_regularizer=regularizers.l2(1e-3)),
            layers.Activation("relu"),
            layers.BatchNormalization(),
            layers.MaxPooling2D(),
            layers.Conv2D(filters=128, kernel_size=3, padding="same",
                           kernel_regularizer=regularizers.l2(1e-3)),
            layers.Activation("relu"),
            layers.BatchNormalization(),
            layers.MaxPooling2D(),
            layers.Conv2D(filters=256, kernel_size=3, padding="same",
                           kernel_regularizer=regularizers.l2(1e-3)),
            layers.Activation("relu"),
            layers.BatchNormalization(),
            # layers.MaxPooling2D(),
            # layers.Flatten(),
            layers.GlobalAveragePooling2D(),
            layers.Dense(units=hidden_size, kernel_regularizer=regularizers.
↪l2(1e-3)),
            layers.Activation("relu"),
            layers.BatchNormalization(),
            layers.Dropout(0.5),
            layers.Dense(units=num_classes, activation='softmax')
        ]
    )
    return model
```

```
[ ]: model = architecture_2()
model.summary()
```

Model: "model_cnn_3"

Layer (type)	Output Shape	Param #
conv2d_12 (Conv2D)	(None, 128, 128, 16)	448
activation (Activation)	(None, 128, 128, 16)	0
batch_normalization (Batch Normalization)	(None, 128, 128, 16)	64
max_pooling2d_12 (MaxPooling2D)	(None, 64, 64, 16)	0
conv2d_13 (Conv2D)	(None, 64, 64, 32)	4640
activation_1 (Activation)	(None, 64, 64, 32)	0
batch_normalization_1 (Batch Normalization)	(None, 64, 64, 32)	128
max_pooling2d_13 (MaxPooling2D)	(None, 32, 32, 32)	0
conv2d_14 (Conv2D)	(None, 32, 32, 64)	18496
activation_2 (Activation)	(None, 32, 32, 64)	0
batch_normalization_2 (Batch Normalization)	(None, 32, 32, 64)	256
max_pooling2d_14 (MaxPooling2D)	(None, 16, 16, 64)	0
conv2d_15 (Conv2D)	(None, 16, 16, 128)	73856
activation_3 (Activation)	(None, 16, 16, 128)	0
batch_normalization_3 (Batch Normalization)	(None, 16, 16, 128)	512
max_pooling2d_15 (MaxPooling2D)	(None, 8, 8, 128)	0

conv2d_16 (Conv2D)	(None, 8, 8, 256)	295168
activation_4 (Activation)	(None, 8, 8, 256)	0
batch_normalization_4 (Batch Normalization)	(None, 8, 8, 256)	1024
global_average_pooling2d (Global Average Pooling2D)	(None, 256)	0
dense_11 (Dense)	(None, 256)	65792
activation_5 (Activation)	(None, 256)	0
batch_normalization_5 (Batch Normalization)	(None, 256)	1024
dropout (Dropout)	(None, 256)	0
dense_12 (Dense)	(None, 4)	1028

```

=====
Total params: 462,436
Trainable params: 460,932
Non-trainable params: 1,504
-----

```

```

[ ]: def compile_train_v2(model, train_ds, val_ds, epochs=10, ckpt_path="/tmp/
    ↪checkpoint"):
        callbacks = [
            keras.callbacks.ReduceLROnPlateau(
                monitor="val_loss", factor=0.3, patience=5, min_lr=0.00001
            ),
            keras.callbacks.ModelCheckpoint(ckpt_path, save_weights_only=True,
    ↪monitor='val_accuracy', mode='max', save_best_only=True),
            keras.callbacks.EarlyStopping(
                monitor="val_loss", patience=10, min_delta=0.001, mode='min'
            )
        ]
        model.compile(optimizer='adam',
                        loss='categorical_crossentropy',
                        metrics=['accuracy'])
        model_fit = model.fit(train_ds, validation_data=val_ds, epochs=epochs,
    ↪callbacks=callbacks)
        return model_fit

```

```

[ ]: model_fit = compile_train_v2(model, train_data, val_data, epochs=100)

```

Epoch 1/100
79/79 [=====] - 57s 252ms/step - loss: 1.4031 - accuracy: 0.7316 - val_loss: 2.0937 - val_accuracy: 0.2885 - lr: 0.0010
Epoch 2/100
79/79 [=====] - 16s 198ms/step - loss: 1.1507 - accuracy: 0.7905 - val_loss: 3.3518 - val_accuracy: 0.2869 - lr: 0.0010
Epoch 3/100
79/79 [=====] - 15s 193ms/step - loss: 1.0578 - accuracy: 0.8108 - val_loss: 3.3650 - val_accuracy: 0.2869 - lr: 0.0010
Epoch 4/100
79/79 [=====] - 17s 217ms/step - loss: 0.9789 - accuracy: 0.8395 - val_loss: 3.1273 - val_accuracy: 0.3974 - lr: 0.0010
Epoch 5/100
79/79 [=====] - 15s 197ms/step - loss: 0.9097 - accuracy: 0.8423 - val_loss: 1.6772 - val_accuracy: 0.6362 - lr: 0.0010
Epoch 6/100
79/79 [=====] - 15s 188ms/step - loss: 0.8235 - accuracy: 0.8686 - val_loss: 1.1002 - val_accuracy: 0.7324 - lr: 0.0010
Epoch 7/100
79/79 [=====] - 15s 197ms/step - loss: 0.8024 - accuracy: 0.8634 - val_loss: 1.5149 - val_accuracy: 0.6795 - lr: 0.0010
Epoch 8/100
79/79 [=====] - 16s 209ms/step - loss: 0.7534 - accuracy: 0.8710 - val_loss: 0.8542 - val_accuracy: 0.8269 - lr: 0.0010
Epoch 9/100
79/79 [=====] - 15s 185ms/step - loss: 0.7138 - accuracy: 0.8849 - val_loss: 1.0785 - val_accuracy: 0.7660 - lr: 0.0010
Epoch 10/100
79/79 [=====] - 15s 186ms/step - loss: 0.7190 - accuracy: 0.8690 - val_loss: 0.8907 - val_accuracy: 0.7997 - lr: 0.0010
Epoch 11/100
79/79 [=====] - 16s 197ms/step - loss: 0.6739 - accuracy: 0.8793 - val_loss: 0.6604 - val_accuracy: 0.8606 - lr: 0.0010
Epoch 12/100
79/79 [=====] - 17s 214ms/step - loss: 0.5940 - accuracy: 0.8937 - val_loss: 0.9059 - val_accuracy: 0.7901 - lr: 0.0010
Epoch 13/100
79/79 [=====] - 15s 185ms/step - loss: 0.6075 - accuracy: 0.8813 - val_loss: 1.9894 - val_accuracy: 0.6042 - lr: 0.0010
Epoch 14/100
79/79 [=====] - 16s 200ms/step - loss: 0.5779 - accuracy: 0.8969 - val_loss: 0.6311 - val_accuracy: 0.8702 - lr: 0.0010
Epoch 15/100
79/79 [=====] - 14s 184ms/step - loss: 0.5427 - accuracy: 0.8945 - val_loss: 1.0864 - val_accuracy: 0.7179 - lr: 0.0010
Epoch 16/100
79/79 [=====] - 15s 188ms/step - loss: 0.5171 - accuracy: 0.9040 - val_loss: 0.6464 - val_accuracy: 0.8686 - lr: 0.0010

Epoch 17/100
79/79 [=====] - 15s 195ms/step - loss: 0.5206 - accuracy: 0.8961 - val_loss: 0.9048 - val_accuracy: 0.8061 - lr: 0.0010
Epoch 18/100
79/79 [=====] - 15s 184ms/step - loss: 0.4534 - accuracy: 0.9132 - val_loss: 0.5772 - val_accuracy: 0.8606 - lr: 0.0010
Epoch 19/100
79/79 [=====] - 17s 210ms/step - loss: 0.4527 - accuracy: 0.9080 - val_loss: 1.6042 - val_accuracy: 0.6619 - lr: 0.0010
Epoch 20/100
79/79 [=====] - 16s 198ms/step - loss: 0.4565 - accuracy: 0.9040 - val_loss: 0.6638 - val_accuracy: 0.8446 - lr: 0.0010
Epoch 21/100
79/79 [=====] - 15s 186ms/step - loss: 0.4240 - accuracy: 0.9168 - val_loss: 0.7386 - val_accuracy: 0.8429 - lr: 0.0010
Epoch 22/100
79/79 [=====] - 15s 186ms/step - loss: 0.4046 - accuracy: 0.9259 - val_loss: 0.5377 - val_accuracy: 0.8654 - lr: 0.0010
Epoch 23/100
79/79 [=====] - 16s 207ms/step - loss: 0.3694 - accuracy: 0.9311 - val_loss: 0.7265 - val_accuracy: 0.8061 - lr: 0.0010
Epoch 24/100
79/79 [=====] - 15s 186ms/step - loss: 0.3969 - accuracy: 0.9207 - val_loss: 1.1870 - val_accuracy: 0.7324 - lr: 0.0010
Epoch 25/100
79/79 [=====] - 15s 189ms/step - loss: 0.3671 - accuracy: 0.9303 - val_loss: 0.5352 - val_accuracy: 0.8429 - lr: 0.0010
Epoch 26/100
79/79 [=====] - 16s 198ms/step - loss: 0.3956 - accuracy: 0.9128 - val_loss: 0.6565 - val_accuracy: 0.7933 - lr: 0.0010
Epoch 27/100
79/79 [=====] - 17s 217ms/step - loss: 0.3453 - accuracy: 0.9307 - val_loss: 0.6613 - val_accuracy: 0.8413 - lr: 0.0010
Epoch 28/100
79/79 [=====] - 17s 215ms/step - loss: 0.3260 - accuracy: 0.9454 - val_loss: 0.7325 - val_accuracy: 0.8365 - lr: 0.0010
Epoch 29/100
79/79 [=====] - 16s 196ms/step - loss: 0.3103 - accuracy: 0.9506 - val_loss: 0.9963 - val_accuracy: 0.7580 - lr: 0.0010
Epoch 30/100
79/79 [=====] - 17s 215ms/step - loss: 0.3166 - accuracy: 0.9462 - val_loss: 1.1952 - val_accuracy: 0.8045 - lr: 0.0010
Epoch 31/100
79/79 [=====] - 15s 186ms/step - loss: 0.2458 - accuracy: 0.9741 - val_loss: 0.4891 - val_accuracy: 0.8942 - lr: 3.0000e-04
Epoch 32/100
79/79 [=====] - 16s 207ms/step - loss: 0.2145 - accuracy: 0.9809 - val_loss: 0.4606 - val_accuracy: 0.8974 - lr: 3.0000e-04

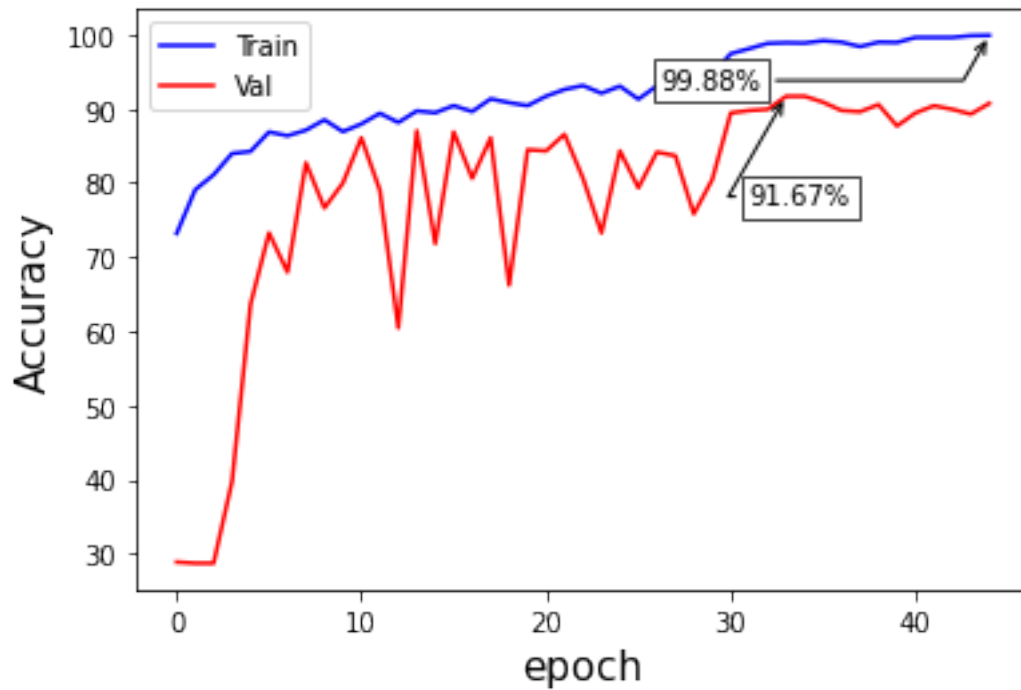
Epoch 33/100
79/79 [=====] - 15s 187ms/step - loss: 0.1888 - accuracy: 0.9881 - val_loss: 0.4501 - val_accuracy: 0.8990 - lr: 3.0000e-04
Epoch 34/100
79/79 [=====] - 16s 198ms/step - loss: 0.1806 - accuracy: 0.9888 - val_loss: 0.4568 - val_accuracy: 0.9167 - lr: 3.0000e-04
Epoch 35/100
79/79 [=====] - 15s 196ms/step - loss: 0.1770 - accuracy: 0.9885 - val_loss: 0.4363 - val_accuracy: 0.9167 - lr: 3.0000e-04
Epoch 36/100
79/79 [=====] - 15s 186ms/step - loss: 0.1687 - accuracy: 0.9916 - val_loss: 0.4505 - val_accuracy: 0.9087 - lr: 3.0000e-04
Epoch 37/100
79/79 [=====] - 15s 185ms/step - loss: 0.1679 - accuracy: 0.9896 - val_loss: 0.5235 - val_accuracy: 0.8974 - lr: 3.0000e-04
Epoch 38/100
79/79 [=====] - 15s 185ms/step - loss: 0.1819 - accuracy: 0.9837 - val_loss: 0.4790 - val_accuracy: 0.8958 - lr: 3.0000e-04
Epoch 39/100
79/79 [=====] - 16s 207ms/step - loss: 0.1583 - accuracy: 0.9896 - val_loss: 0.4875 - val_accuracy: 0.9054 - lr: 3.0000e-04
Epoch 40/100
79/79 [=====] - 15s 184ms/step - loss: 0.1573 - accuracy: 0.9892 - val_loss: 0.5203 - val_accuracy: 0.8766 - lr: 3.0000e-04
Epoch 41/100
79/79 [=====] - 14s 183ms/step - loss: 0.1400 - accuracy: 0.9960 - val_loss: 0.4708 - val_accuracy: 0.8942 - lr: 9.0000e-05
Epoch 42/100
79/79 [=====] - 15s 196ms/step - loss: 0.1381 - accuracy: 0.9960 - val_loss: 0.4652 - val_accuracy: 0.9038 - lr: 9.0000e-05
Epoch 43/100
79/79 [=====] - 15s 186ms/step - loss: 0.1357 - accuracy: 0.9960 - val_loss: 0.5053 - val_accuracy: 0.8990 - lr: 9.0000e-05
Epoch 44/100
79/79 [=====] - 15s 193ms/step - loss: 0.1299 - accuracy: 0.9984 - val_loss: 0.5256 - val_accuracy: 0.8926 - lr: 9.0000e-05
Epoch 45/100
79/79 [=====] - 16s 208ms/step - loss: 0.1265 - accuracy: 0.9988 - val_loss: 0.4670 - val_accuracy: 0.9071 - lr: 9.0000e-05

```
[ ]: # model_fit = model.fit(
#     train_data,
#     steps_per_epoch=train_data.samples//train_data.batch_size, # set the
#     validation_data=val_data,
#     validation_steps=val_data.samples//val_data.batch_size, # set the
#     validation_steps
```

```
# epochs=10 # set the number of epochs
# )
```

```
[ ]:
```

```
[ ]: plot_accuracy(model_fit)
```



```
[ ]: test_loss, test_acc = model.evaluate(test_data)

print('Test accuracy:', test_acc)

print()
print()

y_true = test_data.labels
y_pred = np.argmax(model.predict(test_data), axis=-1)

from sklearn.metrics import classification_report, confusion_matrix

cm = confusion_matrix(y_true, y_pred)
```

```

print('Confusion matrix:')
print(cm)

# Print the classification report
class_names = list(train_data.class_indices.keys())
report = classification_report(y_true, y_pred, target_names=class_names)
print('Classification report:')
print(report)

print()
print()
print()
print()

# Plot confusion matrix
plt.matshow(cm)
plt.title('Confusion matrix')
plt.colorbar()
plt.xlabel('Predicted label')
plt.ylabel('True label')
plt.xticks(np.arange(len(class_names)), class_names, rotation=45)
plt.yticks(np.arange(len(class_names)), class_names)

# Add text annotations to confusion matrix
for i in range(cm.shape[0]):
    for j in range(cm.shape[1]):
        plt.text(j, i, cm[i, j], ha='center', va='center', color='white')

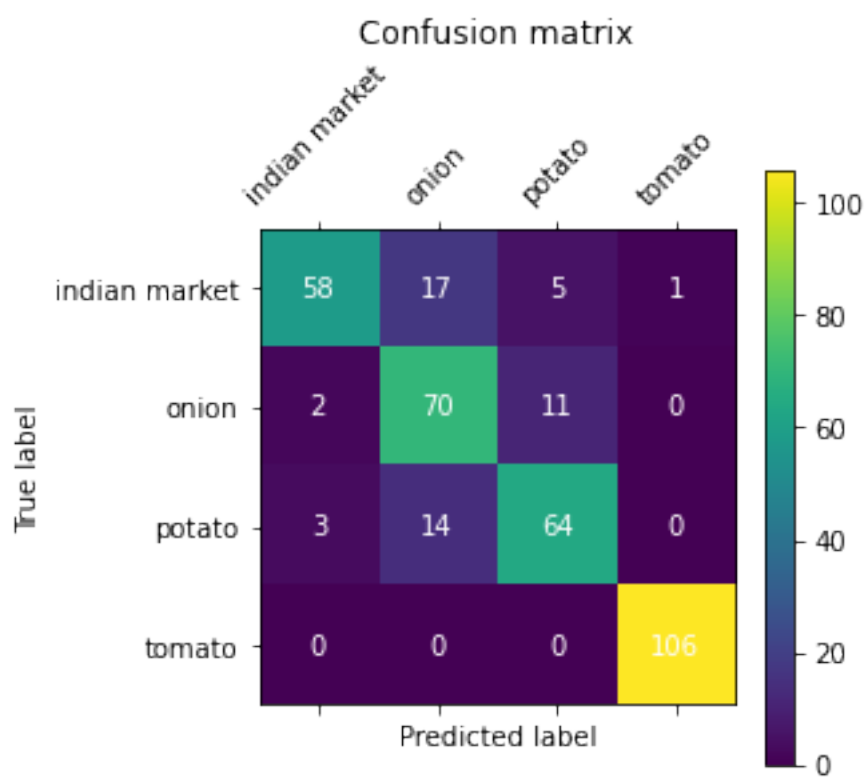
plt.show()

```

11/11 [=====] - 4s 315ms/step - loss: 0.6415 -
accuracy: 0.8490
Test accuracy: 0.8490028381347656

11/11 [=====] - 2s 149ms/step
Confusion matrix:
[[58 17 5 1]
[2 70 11 0]
[3 14 64 0]
[0 0 0 106]]
Classification report:
precision recall f1-score support

indian market	0.92	0.72	0.81	81
onion	0.69	0.84	0.76	83
potato	0.80	0.79	0.80	81
tomato	0.99	1.00	1.00	106
accuracy			0.85	351
macro avg	0.85	0.84	0.84	351
weighted avg	0.86	0.85	0.85	351



[]:

[]:

8.2.1 Functions :

```
[ ]: def plot_acc_loss(model_history, n_epochs):

    fig, axes = plt.subplots(nrows=1, ncols=2,figsize=(15,5))
    ax = axes.ravel()

    #accuracy graph
    ax[0].plot(range(0, n_epochs), [acc * 100 for acc in model_history.
    ↪history['accuracy']], label='Train', color='b')
    ax[0].plot(range(0, n_epochs), [acc * 100 for acc in model_history.
    ↪history['val_accuracy']], label='Val', color='r')
    ax[0].set_title('Accuracy vs. epoch', fontsize=15)
    ax[0].set_ylabel('Accuracy', fontsize=15)
    ax[0].set_xlabel('epoch', fontsize=15)
    ax[0].legend()

    #loss graph
    ax[1].plot(range(0, n_epochs), model_history.history['loss'], label='Train',
    ↪color='b')
    ax[1].plot(range(0, n_epochs), model_history.history['val_loss'],
    ↪label='Val', color='r')
    ax[1].set_title('Loss vs. epoch', fontsize=15)
    ax[1].set_ylabel('Loss', fontsize=15)
    ax[1].set_xlabel('epoch', fontsize=15)
    ax[1].legend()

    #display the graph
    plt.show()

def conf_mat(class_path, pred_list, model_name) :
    noise, tomato, potato, onion = 0, 0, 0, 0
    for i in os.listdir(class_path):

        img = tf.keras.utils.load_img(class_path + "/" + str(i))
        img = tf.keras.utils.img_to_array(img)
        img = tf.image.resize(img, (256, 256))
        img = tf.expand_dims(img, axis = 0)

        pred = model_name.predict(img)
        predicted = tf.argmax(pred, 1).numpy().item()

        if predicted == 0:
            noise+= 1
        elif predicted == 1:
            onion+= 1
```

```

        elif predicted == 2:
            potato+= 1
        else:
            tomato+= 1

    for item in noise, onion, potato, tomato :
        pred_list.append(item)

```

```
[ ]:
```

```
[ ]: ##
```

8.3 Pre-processing :

```
[ ]: train_dir = '/content/ninjacart_data/train'
    test_dir = '/content/ninjacart_data/test'
```

```
[ ]: # Specifying the image size to resize all images
    image_size = (256, 256)
```

```
[ ]: train_ds = tf.keras.utils.image_dataset_from_directory(directory = train_dir,
                                                            label_mode = 'categorical',
                                                            batch_size = 32,
                                                            image_size = image_size,
                                                            seed = 2022,
                                                            validation_split = 0.2,
                                                            subset = "training",
                                                            shuffle=True)
```

Found 3135 files belonging to 4 classes.
Using 2508 files for training.

```
[ ]: test_ds = tf.keras.utils.image_dataset_from_directory(directory = test_dir,
                                                            label_mode = 'categorical',
                                                            batch_size = 32,
                                                            image_size = image_size,
                                                            seed = 2022,
                                                            )
```

Found 351 files belonging to 4 classes.

```
[ ]: valid_ds = tf.keras.utils.image_dataset_from_directory(directory = train_dir,
                                                            label_mode = 'categorical',
```

```

batch_size = 32,
image_size = image_size,
seed = 2022,
validation_split = 0.2,
subset = "validation")

```

Found 3135 files belonging to 4 classes.
Using 627 files for validation.

```
[ ]: class_names = ['indian market', 'onion', 'potato', 'tomato']
```

```
[ ]: augmentation = tf.keras.Sequential([
    tf.keras.layers.RandomFlip("horizontal_and_vertical"),
    tf.keras.layers.RandomRotation(0.2),
    tf.keras.layers.RandomTranslation(height_factor = 0.2, width_factor=0.2)
])

aug_ds = train_ds

for image, label in aug_ds :
    image = augmentation(image)
```

8.4 VGG-19

```
[ ]: base_model_3 = tf.keras.applications.vgg19.VGG19(input_shape=(256, 256, 3),
    ↳include_top = False)
```

Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/vgg19/vgg19_weights_tf_dim_ordering_tf_kernels_notop.h5
80134624/80134624 [=====] - 4s 0us/step

```
[ ]: # append classification layer
model_3 = base_model_3.output

model_3 = tf.keras.Sequential([
    tf.keras.layers.Rescaling(1./255),
    tf.keras.layers.InputLayer(input_shape=[image_size[0],
    ↳image_size[1], 3]),
    base_model_3,
    tf.keras.layers.GlobalAveragePooling2D(),
    tf.keras.layers.Dropout(rate = 0.1),
    tf.keras.layers.Dense(4, activation = 'softmax')
])
```

```
[ ]: model_3.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
rescaling (Rescaling)	(None, 256, 256, 3)	0
input_2 (InputLayer)	multiple	0
vgg19 (Functional)	(None, 8, 8, 512)	20024384
global_average_pooling2d (GlobalAveragePooling2D)	(None, 512)	0
dropout (Dropout)	(None, 512)	0
dense (Dense)	(None, 4)	2052

```

=====
Total params: 20,026,436
Trainable params: 20,026,436
Non-trainable params: 0
=====

```

```
[ ]: model_3.compile(
    optimizer = tf.keras.optimizers.Adam(learning_rate = 1e-4),
    loss = tf.keras.losses.CategoricalCrossentropy(),
    metrics = ['accuracy', 'Precision', 'Recall']
)
```

```
[ ]: log_dir_5 = "logs/VGG19"

tensorboard_cb = tf.keras.callbacks.TensorBoard(log_dir=log_dir_5,
    histogram_freq=1)

checkpoint_cb = tf.keras.callbacks.ModelCheckpoint("VGG19", save_best_only=True)

early_stopping_cb = tf.keras.callbacks.EarlyStopping(
    monitor = 'val_loss', patience = 5, restore_best_weights=True
)
```

```
[ ]: history_3 = model_3.fit(aug_ds,
    validation_data = valid_ds,
    epochs = 25,
    callbacks=[tensorboard_cb,
    checkpoint_cb,
    early_stopping_cb])
```

```
Epoch 1/25
79/79 [=====] - ETA: 0s - loss: 0.6744 - accuracy:
```

0.7113 - precision: 0.7988 - recall: 0.6124

WARNING:absl:Found untraced functions such as _jit_compiled_convolution_op, _jit_compiled_convolution_op, _jit_compiled_convolution_op, _jit_compiled_convolution_op while saving (showing 5 of 16). These functions will not be directly callable after loading.

79/79 [=====] - 78s 980ms/step - loss: 0.6744 - accuracy: 0.7113 - precision: 0.7988 - recall: 0.6124 - val_loss: 0.3900 - val_accuracy: 0.8469 - val_precision: 0.8846 - val_recall: 0.8070

Epoch 2/25

79/79 [=====] - ETA: 0s - loss: 0.3148 - accuracy: 0.8800 - precision: 0.8937 - recall: 0.8652

WARNING:absl:Found untraced functions such as _jit_compiled_convolution_op, _jit_compiled_convolution_op, _jit_compiled_convolution_op, _jit_compiled_convolution_op while saving (showing 5 of 16). These functions will not be directly callable after loading.

79/79 [=====] - 67s 835ms/step - loss: 0.3148 - accuracy: 0.8800 - precision: 0.8937 - recall: 0.8652 - val_loss: 0.2839 - val_accuracy: 0.8963 - val_precision: 0.9130 - val_recall: 0.8868

Epoch 3/25

79/79 [=====] - ETA: 0s - loss: 0.2199 - accuracy: 0.9250 - precision: 0.9305 - recall: 0.9187

WARNING:absl:Found untraced functions such as _jit_compiled_convolution_op, _jit_compiled_convolution_op, _jit_compiled_convolution_op, _jit_compiled_convolution_op while saving (showing 5 of 16). These functions will not be directly callable after loading.

79/79 [=====] - 65s 817ms/step - loss: 0.2199 - accuracy: 0.9250 - precision: 0.9305 - recall: 0.9187 - val_loss: 0.2344 - val_accuracy: 0.9330 - val_precision: 0.9389 - val_recall: 0.9314

Epoch 4/25

79/79 [=====] - 61s 770ms/step - loss: 0.1912 - accuracy: 0.9250 - precision: 0.9329 - recall: 0.9207 - val_loss: 0.2357 - val_accuracy: 0.9266 - val_precision: 0.9326 - val_recall: 0.9266

Epoch 5/25

79/79 [=====] - 60s 753ms/step - loss: 0.1846 - accuracy: 0.9378 - precision: 0.9451 - recall: 0.9334 - val_loss: 0.2452 - val_accuracy: 0.9378 - val_precision: 0.9438 - val_recall: 0.9378

Epoch 6/25

79/79 [=====] - ETA: 0s - loss: 0.1476 - accuracy: 0.9533 - precision: 0.9574 - recall: 0.9502

WARNING:absl:Found untraced functions such as _jit_compiled_convolution_op, _jit_compiled_convolution_op, _jit_compiled_convolution_op, _jit_compiled_convolution_op while saving (showing 5 of 16). These functions will not be directly callable after loading.

```
79/79 [=====] - 65s 811ms/step - loss: 0.1476 -  
accuracy: 0.9533 - precision: 0.9574 - recall: 0.9502 - val_loss: 0.2186 -  
val_accuracy: 0.9474 - val_precision: 0.9503 - val_recall: 0.9458
```

Epoch 7/25

```
79/79 [=====] - 62s 774ms/step - loss: 0.1294 -  
accuracy: 0.9533 - precision: 0.9556 - recall: 0.9518 - val_loss: 0.2742 -  
val_accuracy: 0.9107 - val_precision: 0.9165 - val_recall: 0.9107
```

Epoch 8/25

```
79/79 [=====] - ETA: 0s - loss: 0.0761 - accuracy:  
0.9713 - precision: 0.9751 - recall: 0.9697
```

WARNING:absl:Found untraced functions such as _jit_compiled_convolution_op, _jit_compiled_convolution_op, _jit_compiled_convolution_op, _jit_compiled_convolution_op while saving (showing 5 of 16). These functions will not be directly callable after loading.

```
79/79 [=====] - 65s 813ms/step - loss: 0.0761 -  
accuracy: 0.9713 - precision: 0.9751 - recall: 0.9697 - val_loss: 0.1762 -  
val_accuracy: 0.9649 - val_precision: 0.9696 - val_recall: 0.9649
```

Epoch 9/25

```
79/79 [=====] - 61s 767ms/step - loss: 0.1255 -  
accuracy: 0.9577 - precision: 0.9611 - recall: 0.9545 - val_loss: 0.1778 -  
val_accuracy: 0.9553 - val_precision: 0.9599 - val_recall: 0.9553
```

Epoch 10/25

```
79/79 [=====] - 60s 753ms/step - loss: 0.1216 -  
accuracy: 0.9581 - precision: 0.9614 - recall: 0.9545 - val_loss: 0.2304 -  
val_accuracy: 0.9250 - val_precision: 0.9337 - val_recall: 0.9203
```

Epoch 11/25

```
79/79 [=====] - 61s 759ms/step - loss: 0.0894 -  
accuracy: 0.9665 - precision: 0.9687 - recall: 0.9629 - val_loss: 0.3555 -  
val_accuracy: 0.9091 - val_precision: 0.9109 - val_recall: 0.8963
```

Epoch 12/25

```
79/79 [=====] - 60s 757ms/step - loss: 0.0811 -  
accuracy: 0.9713 - precision: 0.9724 - recall: 0.9697 - val_loss: 0.1950 -  
val_accuracy: 0.9633 - val_precision: 0.9633 - val_recall: 0.9617
```

Epoch 13/25

```
79/79 [=====] - 60s 756ms/step - loss: 0.0680 -  
accuracy: 0.9793 - precision: 0.9812 - recall: 0.9785 - val_loss: 0.2065 -  
val_accuracy: 0.9458 - val_precision: 0.9473 - val_recall: 0.9458
```

```
[ ]: def classwise_accuracy(class_path, class_name, model_name) :  
    paths = []  
    for i in os.listdir(class_path):  
        paths.append(class_path + "/" + str(i))  
  
    correct = 0  
    total = 0
```

```

for i in range(len(paths)):
    total+= 1

    img = tf.keras.utils.load_img(paths[i])
    img = tf.keras.utils.img_to_array(img)
    img = tf.image.resize(img, (256, 256))
    img = tf.expand_dims(img, axis = 0)

    pred = model_name.predict(img,verbose=0)
    if tf.argmax(pred[0]) == class_names.index(f"{class_name}"):
        correct+= 1

    print(f"Accuracy for class {class_name} is {round((correct/total)*100, 2)}%
    ↳consisting of {len(paths)} images")

```

```

[ ]: def plot_acc_loss(model_history, n_epochs):

    fig, axes = plt.subplots(nrows=1, ncols=2,figsize=(15,5))
    ax = axes.ravel()

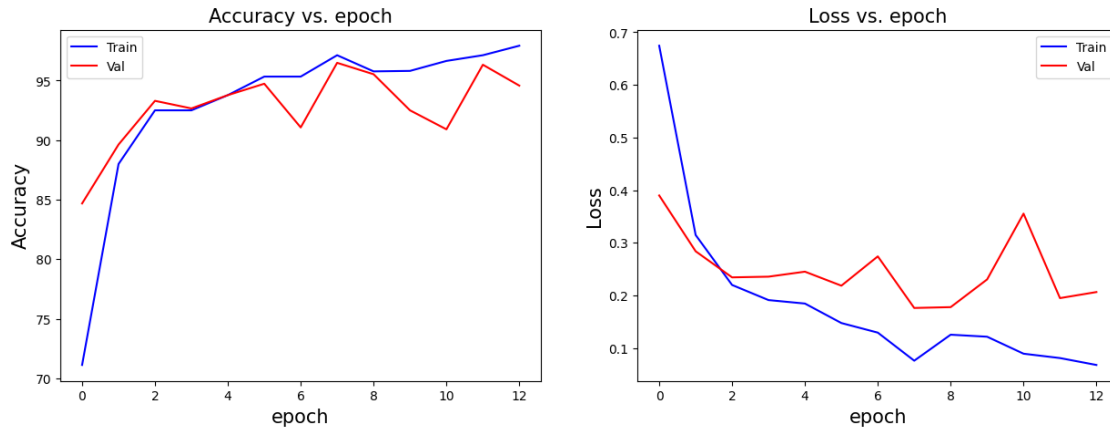
    #accuracy graph
    ax[0].plot(range(0, n_epochs), [acc * 100 for acc in model_history.
    ↳history['accuracy']], label='Train', color='b')
    ax[0].plot(range(0, n_epochs), [acc * 100 for acc in model_history.
    ↳history['val_accuracy']], label='Val', color='r')
    ax[0].set_title('Accuracy vs. epoch', fontsize=15)
    ax[0].set_ylabel('Accuracy', fontsize=15)
    ax[0].set_xlabel('epoch', fontsize=15)
    ax[0].legend()

    #loss graph
    ax[1].plot(range(0, n_epochs), model_history.history['loss'], label='Train',
    ↳color='b')
    ax[1].plot(range(0, n_epochs), model_history.history['val_loss'],
    ↳label='Val', color='r')
    ax[1].set_title('Loss vs. epoch', fontsize=15)
    ax[1].set_ylabel('Loss', fontsize=15)
    ax[1].set_xlabel('epoch', fontsize=15)
    ax[1].legend()

    #display the graph
    plt.show()

plot_acc_loss(history_3, n_epochs = 13)

```



```
[ ]: noise_path = '/content/ninjacart_data/test/indian market'
onion_path = '/content/ninjacart_data/test/onion'
potato_path = '/content/ninjacart_data/test/potato'
tomato_path = '/content/ninjacart_data/test/tomato'

classwise_accuracy(noise_path, 'indian market', model_3)
classwise_accuracy(onion_path, 'onion', model_3)
classwise_accuracy(potato_path, 'potato', model_3)
classwise_accuracy(tomato_path, 'tomato', model_3)
```

Accuracy for class indian market is 87.65% consisting of 81 images
 Accuracy for class onion is 100.0% consisting of 83 images
 Accuracy for class potato is 86.42% consisting of 81 images
 Accuracy for class tomato is 100.0% consisting of 106 images

```
[ ]: def conf_mat(class_path, pred_list, model_name) :
    noise, tomato, potato, onion = 0, 0, 0, 0
    for i in os.listdir(class_path):

        img = tf.keras.utils.load_img(class_path + "/" + str(i))
        img = tf.keras.utils.img_to_array(img)
        img = tf.image.resize(img, (256, 256))
        img = tf.expand_dims(img, axis = 0)

        pred = model_name.predict(img, verbose=0)
        predicted = tf.argmax(pred, 1).numpy().item()

        if predicted == 0:
            noise+= 1
        elif predicted == 1:
            onion+= 1
        elif predicted == 2:
```

```

        potato+= 1
    else:
        tomato+= 1

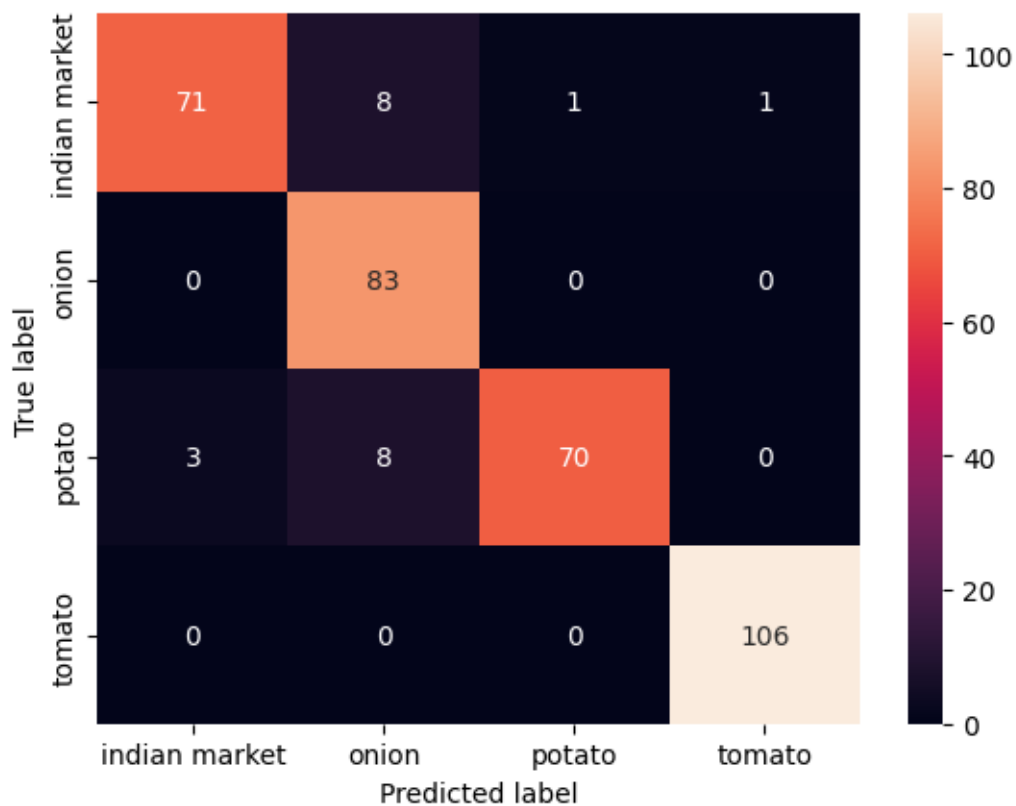
    for item in noise, onion, potato, tomato :
        pred_list.append(item)

l1 = []
l2 = []
l3 = []
l4 = []

conf_mat(noise_path, l1, model_3)
conf_mat(onion_path, l2, model_3)
conf_mat(potato_path, l3, model_3)
conf_mat(tomato_path, l4, model_3)

ax = sns.heatmap([l1, l2, l3, l4], xticklabels=class_names,
                  yticklabels=class_names, annot=True, fmt='g')
ax.set(xlabel='Predicted label', ylabel='True label')
plt.show()

```



```
[ ]: result = model_3.evaluate(test_ds)
      dict(zip(model_3.metrics_names, result))
```

```
11/11 [=====] - 10s 736ms/step - loss: 0.2026 -
accuracy: 0.9402 - precision: 0.9398 - recall: 0.9345
```

```
[ ]: {'loss': 0.20257778465747833,
      'accuracy': 0.94017094373703,
      'precision': 0.939828097820282,
      'recall': 0.934472918510437}
```

```
[ ]:
```

```
[ ]:
```

8.5 ResNet

```
[ ]: base_model_1 = tf.keras.applications.resnet50.ResNet50(input_shape=(256, 256, 3),
      include_top = False)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-
applications/resnet/resnet50_weights_tf_dim_ordering_tf_kernels_notop.h5
94765736/94765736 [=====] - 5s 0us/step
```

```
[ ]: # append classification layer
      model_1 = base_model_1.output

      model_1 = tf.keras.Sequential([
          #Normalizing 0-255 into 0 to 1
          tf.keras.layers.Rescaling(1./255),
          tf.keras.layers.InputLayer(input_shape=[image_size[0],
      image_size[1], 3]),
          base_model_1,
          tf.keras.layers.GlobalAveragePooling2D(),
          tf.keras.layers.Dropout(rate = 0.1),
          tf.keras.layers.Dense(4, activation = 'softmax')
      ])
```

```
[ ]: model_1.compile(optimizer = tf.keras.optimizers.Adam(learning_rate = 1e-4),
      loss = tf.keras.losses.CategoricalCrossentropy(),
      metrics = ['accuracy', 'Precision', 'Recall'])
```

```
[ ]: model_1.summary()
```

```
Model: "sequential_2"
```

```
-----
```

Layer (type)	Output Shape	Param #
rescaling_1 (Rescaling)	(None, 256, 256, 3)	0
input_4 (InputLayer)	multiple	0
resnet50 (Functional)	(None, 8, 8, 2048)	23587712
global_average_pooling2d_1 (GlobalAveragePooling2D)	(None, 2048)	0
dropout_1 (Dropout)	(None, 2048)	0
dense_1 (Dense)	(None, 4)	8196

Total params: 23,595,908
Trainable params: 23,542,788
Non-trainable params: 53,120

```
[ ]: log_dir_3 = "logs/ResNet"

tensorboard_cb = tf.keras.callbacks.TensorBoard(log_dir=log_dir_3,
↪ histogram_freq=1)

checkpoint_cb = tf.keras.callbacks.ModelCheckpoint("ResNet.h5",
↪ save_best_only=True)

early_stopping_cb = tf.keras.callbacks.EarlyStopping(
    monitor = 'val_loss', patience = 5, restore_best_weights=True
)
```

```
[ ]: history_1 = model_1.fit(aug_ds,
                             validation_data = valid_ds,
                             epochs = 20,
                             callbacks=[tensorboard_cb,
                                         checkpoint_cb,
                                         early_stopping_cb])
```

Epoch 1/20

79/79 [=====] - 98s 614ms/step - loss: 0.1930 -
accuracy: 0.9290 - precision: 0.9427 - recall: 0.9183 - val_loss: 3.7173 -
val_accuracy: 0.2121 - val_precision: 0.2121 - val_recall: 0.2121

Epoch 2/20

79/79 [=====] - 42s 529ms/step - loss: 0.0200 -
accuracy: 0.9948 - precision: 0.9948 - recall: 0.9940 - val_loss: 2.1190 -
val_accuracy: 0.2073 - val_precision: 0.2017 - val_recall: 0.1946

Epoch 3/20
79/79 [=====] - 44s 554ms/step - loss: 0.0195 -
accuracy: 0.9960 - precision: 0.9960 - recall: 0.9956 - val_loss: 3.3367 -
val_accuracy: 0.2026 - val_precision: 0.2019 - val_recall: 0.2010

Epoch 4/20
79/79 [=====] - 43s 538ms/step - loss: 0.0069 -
accuracy: 0.9980 - precision: 0.9980 - recall: 0.9980 - val_loss: 4.0221 -
val_accuracy: 0.1914 - val_precision: 0.1920 - val_recall: 0.1914

Epoch 5/20
79/79 [=====] - 41s 509ms/step - loss: 0.0308 -
accuracy: 0.9932 - precision: 0.9932 - recall: 0.9932 - val_loss: 5.3504 -
val_accuracy: 0.1340 - val_precision: 0.1287 - val_recall: 0.1180

Epoch 6/20
79/79 [=====] - 42s 529ms/step - loss: 0.0204 -
accuracy: 0.9932 - precision: 0.9932 - recall: 0.9924 - val_loss: 1.8560 -
val_accuracy: 0.3285 - val_precision: 0.3333 - val_recall: 0.2695

Epoch 7/20
79/79 [=====] - 41s 510ms/step - loss: 0.0223 -
accuracy: 0.9936 - precision: 0.9936 - recall: 0.9932 - val_loss: 2.0921 -
val_accuracy: 0.4545 - val_precision: 0.4742 - val_recall: 0.4402

Epoch 8/20
79/79 [=====] - 42s 522ms/step - loss: 0.0222 -
accuracy: 0.9916 - precision: 0.9920 - recall: 0.9916 - val_loss: 1.8277 -
val_accuracy: 0.5885 - val_precision: 0.6205 - val_recall: 0.5710

Epoch 9/20
79/79 [=====] - 43s 534ms/step - loss: 0.0072 -
accuracy: 0.9980 - precision: 0.9980 - recall: 0.9980 - val_loss: 0.6402 -
val_accuracy: 0.7879 - val_precision: 0.8199 - val_recall: 0.7624

Epoch 10/20
79/79 [=====] - 42s 514ms/step - loss: 0.0085 -
accuracy: 0.9964 - precision: 0.9964 - recall: 0.9964 - val_loss: 1.0781 -
val_accuracy: 0.7719 - val_precision: 0.7833 - val_recall: 0.7608

Epoch 11/20
79/79 [=====] - 43s 532ms/step - loss: 0.0102 -
accuracy: 0.9968 - precision: 0.9968 - recall: 0.9968 - val_loss: 0.5584 -
val_accuracy: 0.8740 - val_precision: 0.8847 - val_recall: 0.8692

Epoch 12/20
79/79 [=====] - 42s 530ms/step - loss: 0.0164 -
accuracy: 0.9960 - precision: 0.9968 - recall: 0.9956 - val_loss: 0.2189 -
val_accuracy: 0.9585 - val_precision: 0.9614 - val_recall: 0.9522

Epoch 13/20
79/79 [=====] - 43s 533ms/step - loss: 0.0079 -
accuracy: 0.9972 - precision: 0.9976 - recall: 0.9972 - val_loss: 0.0962 -
val_accuracy: 0.9697 - val_precision: 0.9743 - val_recall: 0.9665

Epoch 14/20
79/79 [=====] - 41s 513ms/step - loss: 0.0130 -
accuracy: 0.9952 - precision: 0.9952 - recall: 0.9948 - val_loss: 0.3641 -
val_accuracy: 0.9266 - val_precision: 0.9279 - val_recall: 0.9234

Epoch 15/20

79/79 [=====] - 43s 532ms/step - loss: 0.0062 - accuracy: 0.9988 - precision: 0.9988 - recall: 0.9988 - val_loss: 0.1230 - val_accuracy: 0.9697 - val_precision: 0.9712 - val_recall: 0.9681

Epoch 16/20

79/79 [=====] - 42s 529ms/step - loss: 0.0023 - accuracy: 0.9996 - precision: 0.9996 - recall: 0.9996 - val_loss: 0.1020 - val_accuracy: 0.9729 - val_precision: 0.9760 - val_recall: 0.9729

Epoch 17/20

79/79 [=====] - 42s 530ms/step - loss: 0.0035 - accuracy: 0.9988 - precision: 0.9992 - recall: 0.9988 - val_loss: 0.0893 - val_accuracy: 0.9793 - val_precision: 0.9824 - val_recall: 0.9777

Epoch 18/20

79/79 [=====] - 41s 508ms/step - loss: 0.0049 - accuracy: 0.9984 - precision: 0.9984 - recall: 0.9984 - val_loss: 0.2058 - val_accuracy: 0.9697 - val_precision: 0.9712 - val_recall: 0.9697

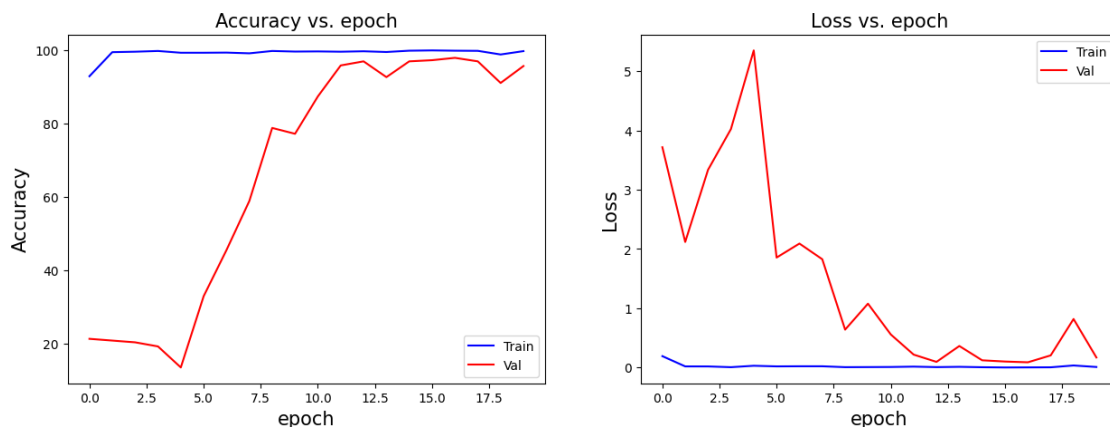
Epoch 19/20

79/79 [=====] - 41s 510ms/step - loss: 0.0356 - accuracy: 0.9884 - precision: 0.9884 - recall: 0.9864 - val_loss: 0.8196 - val_accuracy: 0.9107 - val_precision: 0.9135 - val_recall: 0.9091

Epoch 20/20

79/79 [=====] - 40s 501ms/step - loss: 0.0102 - accuracy: 0.9976 - precision: 0.9976 - recall: 0.9972 - val_loss: 0.1705 - val_accuracy: 0.9569 - val_precision: 0.9569 - val_recall: 0.9553

```
[ ]: plot_acc_loss(history_1, n_epochs = 20)
```



```
[ ]: noise_path = '/content/ninjacart_data/test/indian market'  
onion_path = '/content/ninjacart_data/test/onion'  
potato_path = '/content/ninjacart_data/test/potato'  
tomato_path = '/content/ninjacart_data/test/tomato'
```

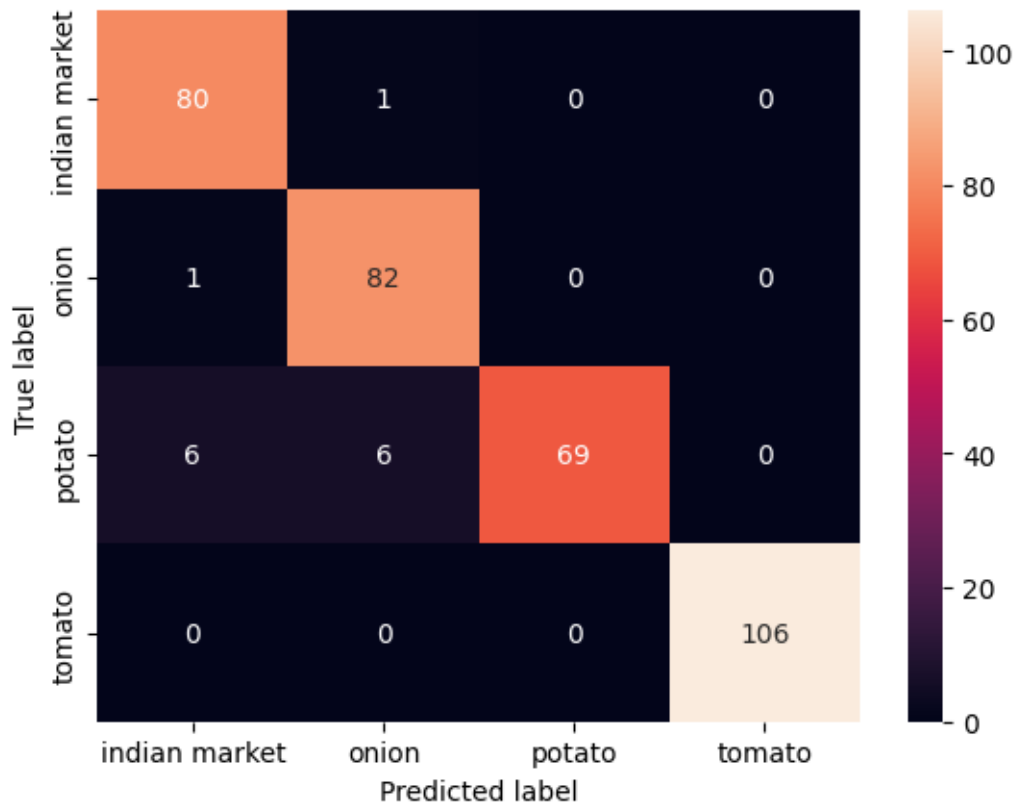
```
classwise_accuracy(noise_path, 'indian market', model_1)
classwise_accuracy(onion_path, 'onion', model_1)
classwise_accuracy(potato_path, 'potato', model_1)
classwise_accuracy(tomato_path, 'tomato', model_1)
```

Accuracy for class indian market is 98.77% consisting of 81 images
Accuracy for class onion is 98.8% consisting of 83 images
Accuracy for class potato is 85.19% consisting of 81 images
Accuracy for class tomato is 100.0% consisting of 106 images

```
[ ]: l1 = []
      l2 = []
      l3 = []
      l4 = []

      conf_mat(noise_path, l1, model_1)
      conf_mat(onion_path, l2, model_1)
      conf_mat(potato_path, l3, model_1)
      conf_mat(tomato_path, l4, model_1)

      ax = sns.heatmap([l1, l2, l3, l4], xticklabels=class_names,
                        yticklabels=class_names, annot=True, fmt='g')
      ax.set(xlabel='Predicted label', ylabel='True label')
      plt.show()
```



```
[ ]: result = model_1.evaluate(test_ds)
dict(zip(model_1.metrics_names, result))
```

```
11/11 [=====] - 4s 262ms/step - loss: 0.1591 -
accuracy: 0.9630 - precision: 0.9628 - recall: 0.9573
```

```
[ ]: {'loss': 0.15911954641342163,
      'accuracy': 0.9629629850387573,
      'precision': 0.9627507328987122,
      'recall': 0.9572649598121643}
```

```
[ ]:
```

```
[ ]: test_ds.class_names
```

```
[ ]: ['indian market', 'onion', 'potato', 'tomato']
```

```
[ ]: test_loss, test_acc, test_precision, test_recall = model_1.evaluate(test_ds)
```

```
11/11 [=====] - 3s 126ms/step - loss: 0.1591 -
accuracy: 0.9630 - precision: 0.9628 - recall: 0.9573
```

```
[ ]: print('Test accuracy:', test_acc)

print()
print()
```

Test accuracy: 0.9629629850387573

```
[ ]:
```

```
[ ]:
```

8.6 Model Comparison:

```
###
ANN
To-
tal
params:
12,649,988
Train-
able
params:
12,649,988
Non-
trainable
params:
0
loss:
1.0572
Test
ac-
cu-
racy:
0.6153846383094788
pre-
ci-
sion:
0.62
re-
call:
0.62
```

8.6.1 CNN

Architecture 1:

Total params: 4,288,196
Trainable params: 4,288,196
Non-trainable params: 0
loss: 0.5620
Test-accuracy: 0.8547
precision: 0.86
recall: 0.85

CNN architecture 2:

Total params: 462,436
Trainable params: 460,932
Non-trainable params: 1,504

loss: 0.6415
Test accuracy: 0.8490028381347656
precision: 0.86
recall: 0.85

8.6.2 VGG-19

Total params: 20,026,436
Trainable params: 20,026,436
Non-trainable params: 0.

loss: 0.2026
Test-accuracy: 0.9402
precision: 0.9398
recall: 0.9345

8.6.3 ResNet50

Total params: 23,595,908
Trainable params: 23,542,788
Non-trainable params: 53,120

loss : 0.1591
Test-accuracy: 0.9630
precision: 0.9628
recall: 0.9573

Model	Test Accuracy
ANN	62%
CNN-1	85%
CNN-2	84%
VGG-19	94%

Model	Test Accuracy
ResNet50	96%

With Model ResNet50 :

Accuracy for class indian market is 98.77% consisting of 81 images
 Accuracy for class onion is 98.8% consisting of 83 images
 Accuracy for class potato is 85.19% consisting of 81 images
 Accuracy for class tomato is 100.0% consisting of 106 images

```
[ ]: %load_ext tensorboard
      %tensorboard --logdir /content/logs
```

Output hidden; open in <https://colab.research.google.com> to view.

```
[ ]:
```

```
[ ]:
```