Ninjacart Business Case:

Business Problem:

- 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.

Dataset:

Context:

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

Data Collection:

- The images in this dataset were scraped from Google.

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

Inspiration:

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

Importing required Libraries and Dataset:

In [1]:
```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
import os
import glob
import random
import shutil

from sklearn import metrics

import tensorflow as tf
from tensorflow.keras import Sequential
from tensorflow.keras.layers import Dense, Dropout, BatchNormalization
from tensorflow.keras import layers, regularizers
from tensorflow.keras.applications import MobileNetV3Large

# For Reproducibility
np.random.seed(42)
tf.random.set_seed(42)
```

In [2]:
```
!python -m wget https://drive.google.com/file/d/1clZX-lV_MLxKHSyeyTheX5OCQtNCUcqT/view
```

```
Saved under view
```

Dividing Train Data into Train and Validation:

In [10]:
```
test_size = 0.2
classes = os.listdir("ninjacart_data/train")
os.mkdir("ninjacart_data/val")
for cls in classes:
    os.mkdir(f"ninjacart_data/val/{cls}")
    file_paths = glob.glob(f'ninjacart_data/train/{cls}/*')
    val_files = random.sample(file_paths, k=int(len(file_paths)*test_size))
    for img in val_files:
        shutil.move(img, f'ninjacart_data/val/{cls}/')
```

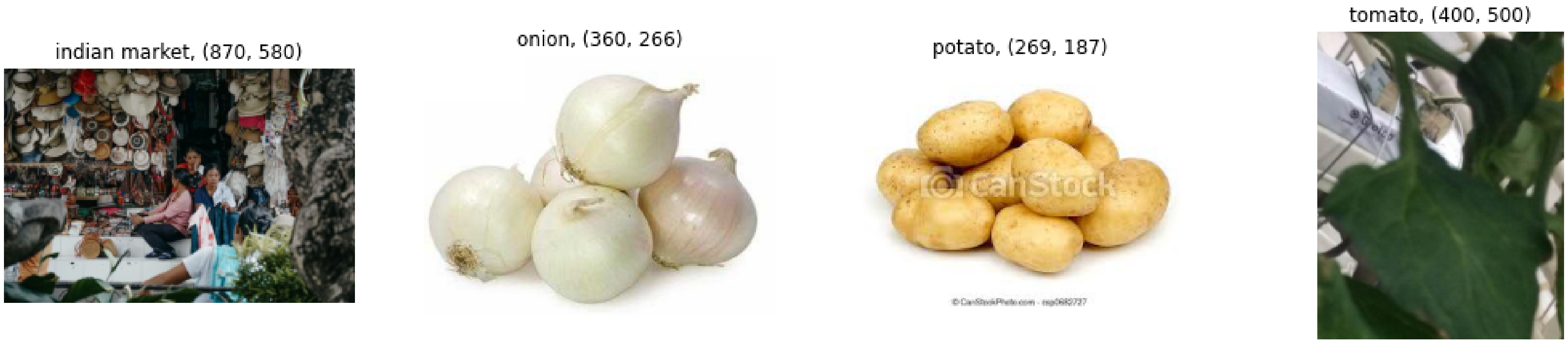
In [ ]:
```

```

Exploratory Data Analysis (EDA):

Plotting images from dataset randomly:

In [11]:
```
class_dirs = os.listdir("ninjacart_data/train") # list all directories inside "train" folder
image_dict = {} # dict to store image array(key) for every class(value)
count_dict = {} # dict to store count of files(key) for every class(value)
# iterate over all class_dirs
for cls in class_dirs:
    # 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
    count_dict[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[cls] = tf.keras.utils.load_img(image_path)
```

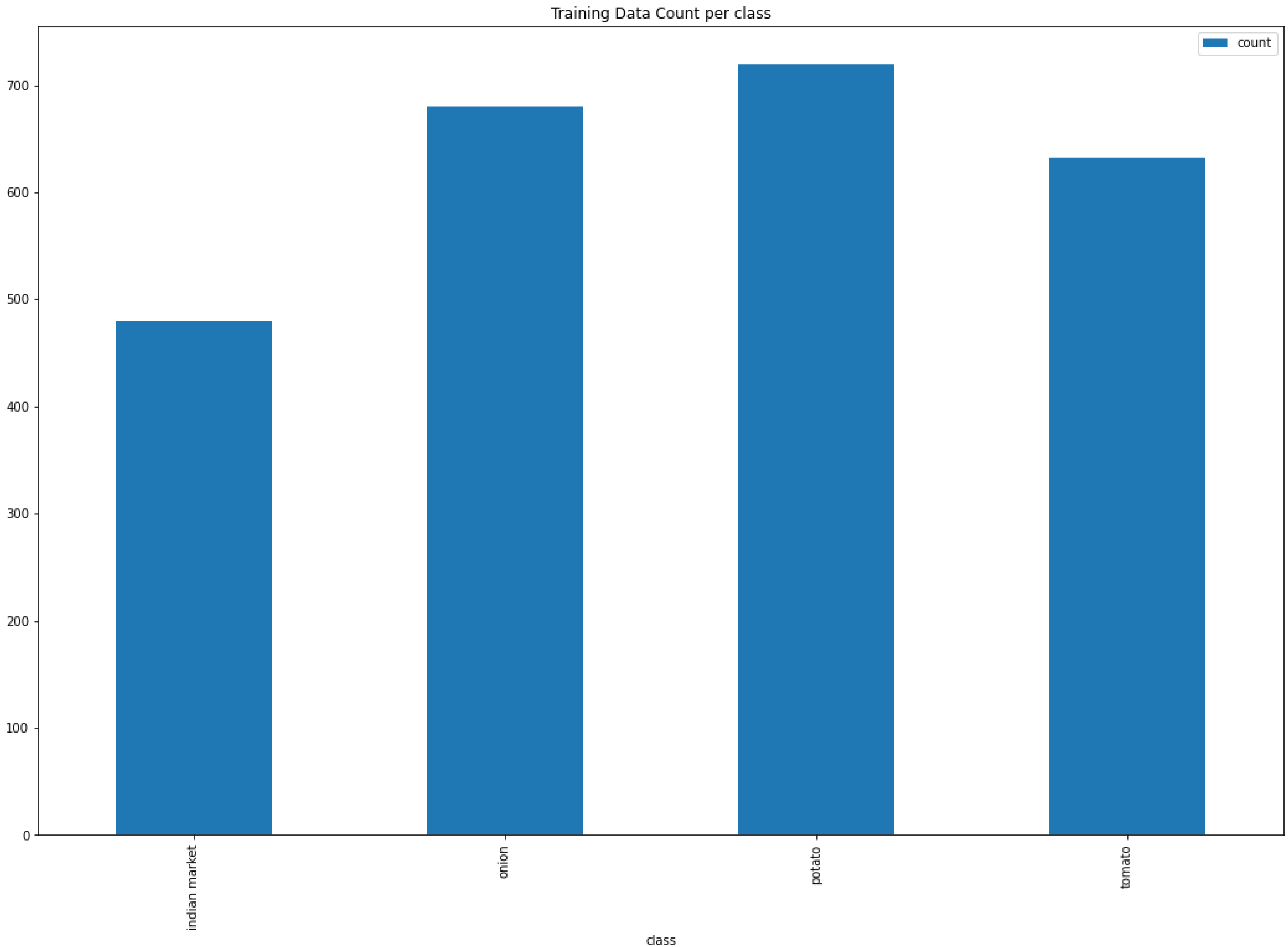
In [13]:
```
## Visualize Random Sample from each class

plt.figure(figsize=(18, 12))
# iterate over dictionary items (class label, image array)
for i, (cls,img) in enumerate(image_dict.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")
```



In [17]:
```
## Let's now Plot the Data Distribution of Training Data across Classes
df_count_train = pd.DataFrame({
    "class": count_dict.keys(), # keys of count_dict are class labels
    "count": count_dict.values(), # value of count_dict contain counts of each class
})
print("Count of training samples per class:\n", df_count_train)

plt.rcParams["figure.figsize"] = (18,12)
# 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  indian market    480
1          onion    680
2         potato    719
3         tomato    632
```

Out[17]:
```
<AxesSubplot:title={'center':'Training Data Count per class'}, xlabel='class'>
```


Training Data Count per class
count
0
100
200
300
400
500
600
700
indian market
onion
potato
tomato
class

In [ ]:

Data Modellig:

Loading data into Keras dataset:

In [18]:
```
def load_data(base_dir="ninjacart_data"):
    # checking if the data folders are present
    assert os.path.exists(f"{base_dir}/train") and os.path.exists(f"{base_dir}/val") and os.path.exists(f"{base_dir}/t

    print('\nLoading Data...')
    train_data = tf.keras.utils.image_dataset_from_directory(
        f"{base_dir}/train", shuffle=True, label_mode='categorical')

    val_data = tf.keras.utils.image_dataset_from_directory(
        f"{base_dir}/val", shuffle=False, label_mode='categorical')

    test_data = tf.keras.utils.image_dataset_from_directory(
        f"{base_dir}/test", shuffle=False, label_mode='categorical')

    return train_data, val_data, test_data, train_data.class_names
```

In [19]:
```
train_data, val_data, test_data, class_names = load_data()
```

```
Loading Data...
Found 2511 files belonging to 4 classes.
Found 624 files belonging to 4 classes.
Found 351 files belonging to 4 classes.
```

In [ ]:

Making all images of Uniform Dimensions and Rescaling:

In [20]:
```
def preprocess(train_data, val_data, test_data, target_height=224, target_width=224):
    # Data Processing Stage with resizing and rescaling operations
    data_preprocess = tf.keras.Sequential(
        name="data_preprocess",
        layers=[
            tf.keras.layers.Resizing(target_height, target_width),
            tf.keras.layers.Rescaling(1.0/255),
        ]
    )
    # Perform Data Processing on the train, val, test dataset
    train_ds = train_data.map(lambda x, y: (data_preprocess(x), y), num_parallel_calls=tf.data.AUTOTUNE)
    val_ds = val_data.map(lambda x, y: (data_preprocess(x), y), num_parallel_calls=tf.data.AUTOTUNE)
    test_ds = test_data.map(lambda x, y: (data_preprocess(x), y), num_parallel_calls=tf.data.AUTOTUNE)

    return train_ds, val_ds, test_ds
```

In [21]:
```
train_ds, val_ds, test_ds = preprocess(train_data, val_data, test_data)
```

In [ ]:

Model Building:

Baseline Model (Defining the CNN Classifier model from scratch):

In [22]:
```
def baseline(height=224, width=224):
    num_classes = 4
    hidden_size = 256

    model = tf.keras.Sequential(
        name="model_cnn",
        layers=[
            tf.keras.layers.Conv2D(filters=16, kernel_size=3, padding="same", activation='relu', input_shape=(height,
            tf.keras.layers.MaxPooling2D(),
            tf.keras.layers.Flatten(),
            tf.keras.layers.Dense(units=hidden_size, activation='relu'),
            tf.keras.layers.Dense(units=num_classes, activation='softmax')
        ]
    )
    return model
```

In [23]:
```
model = baseline()
model.summary()
```

```
Model: "model_cnn"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 224, 224, 16)      448

 max_pooling2d (MaxPooling2D  (None, 112, 112, 16)     0
 )

 flatten (Flatten)           (None, 200704)            0

 dense (Dense)               (None, 256)               51380480

 dense_1 (Dense)             (None, 4)                 1028

=================================================================
Total params: 51,381,956
Trainable params: 51,381,956
Non-trainable params: 0
_________________________________________________________________
```

Compile and Train:

In [27]:
```
def compile_train_v1(model, train_ds, val_ds, ckpt_path="./tmp/checkpoint"):
    epochs = 10
    model.compile(optimizer='adam',
        loss='categorical_crossentropy',
        metrics=['accuracy'])

    model_fit = model.fit(train_ds, validation_data=val_ds, epochs=epochs, callbacks=[
        tf.keras.callbacks.ModelCheckpoint(ckpt_path, save_weights_only=True, monitor='val_accuracy', mode='max', save
    ])

    return model_fit
```

In [28]:
```
model_fit = compile_train_v1(model, train_ds, val_ds)
```

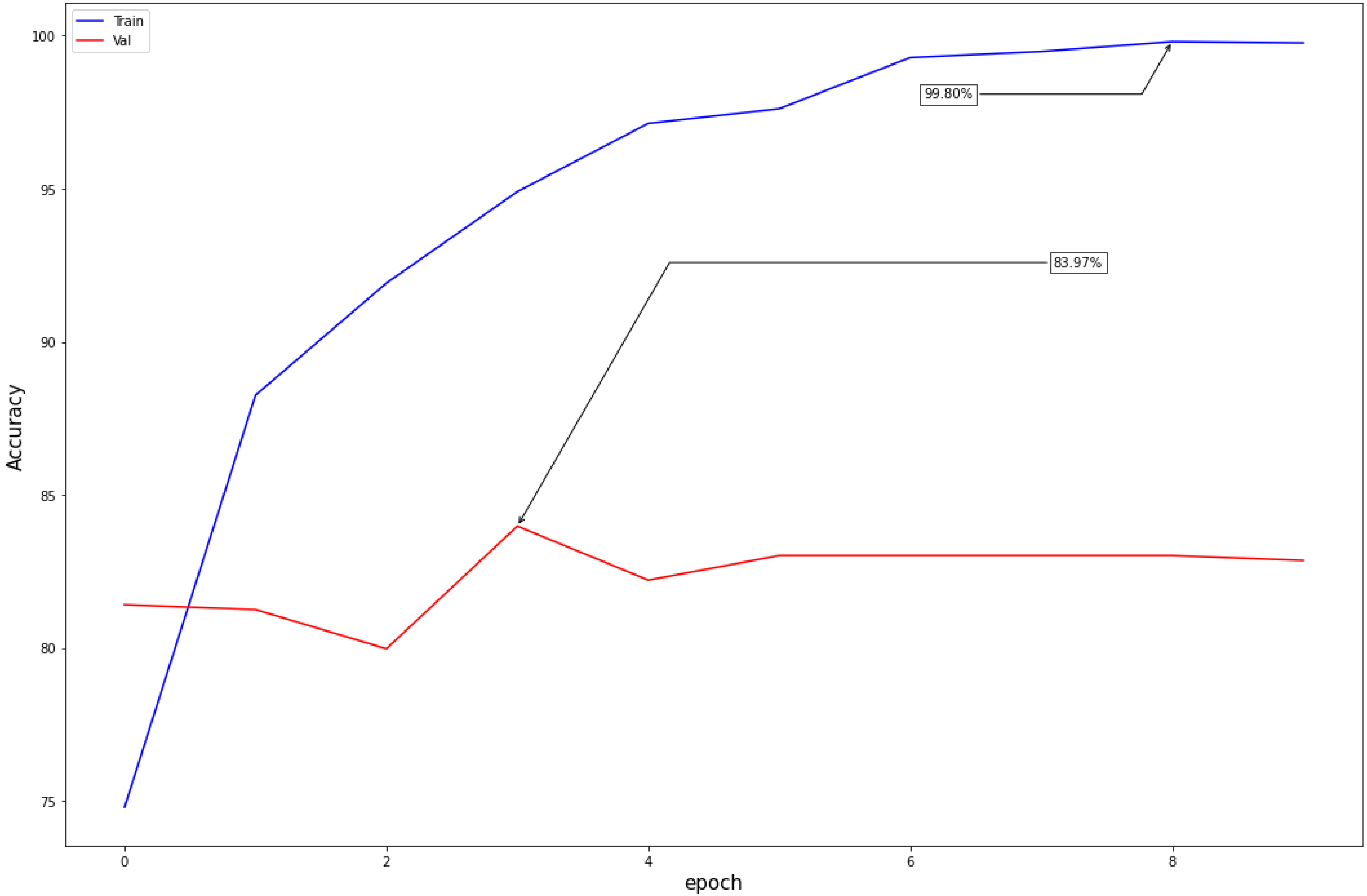
```
Epoch 1/10
79/79 [==============================] - 97s 1s/step - loss: 0.9645 - accuracy: 0.7479 - val_loss: 0.5156 - val_accu
racy: 0.8141
Epoch 2/10
79/79 [==============================] - 81s 1s/step - loss: 0.3517 - accuracy: 0.8825 - val_loss: 0.4793 - val_accu
racy: 0.8125
Epoch 3/10
79/79 [==============================] - 82s 1s/step - loss: 0.2345 - accuracy: 0.9192 - val_loss: 0.5263 - val_accu
racy: 0.7997
Epoch 4/10
79/79 [==============================] - 82s 1s/step - loss: 0.1642 - accuracy: 0.9490 - val_loss: 0.4798 - val_accu
racy: 0.8397
Epoch 5/10
79/79 [==============================] - 82s 1s/step - loss: 0.1034 - accuracy: 0.9713 - val_loss: 0.5235 - val_accu
racy: 0.8221
Epoch 6/10
79/79 [==============================] - 86s 1s/step - loss: 0.0923 - accuracy: 0.9761 - val_loss: 0.5243 - val_accu
racy: 0.8301
Epoch 7/10
79/79 [==============================] - 86s 1s/step - loss: 0.0323 - accuracy: 0.9928 - val_loss: 0.5912 - val_accu
racy: 0.8301
Epoch 8/10
79/79 [==============================] - 86s 1s/step - loss: 0.0188 - accuracy: 0.9948 - val_loss: 0.6266 - val_accu
racy: 0.8301
Epoch 9/10
79/79 [==============================] - 102s 1s/step - loss: 0.0133 - accuracy: 0.9980 - val_loss: 0.6256 - val_acc
uracy: 0.8301
Epoch 10/10
79/79 [==============================] - 97s 1s/step - loss: 0.0113 - accuracy: 0.9976 - val_loss: 0.6750 - val_accu
racy: 0.8285
```

In [ ]:

Plot Train and Validation Accuracy:

In [29]:
```
#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()
```

In [30]:
```
plot_accuracy(model_fit)
```

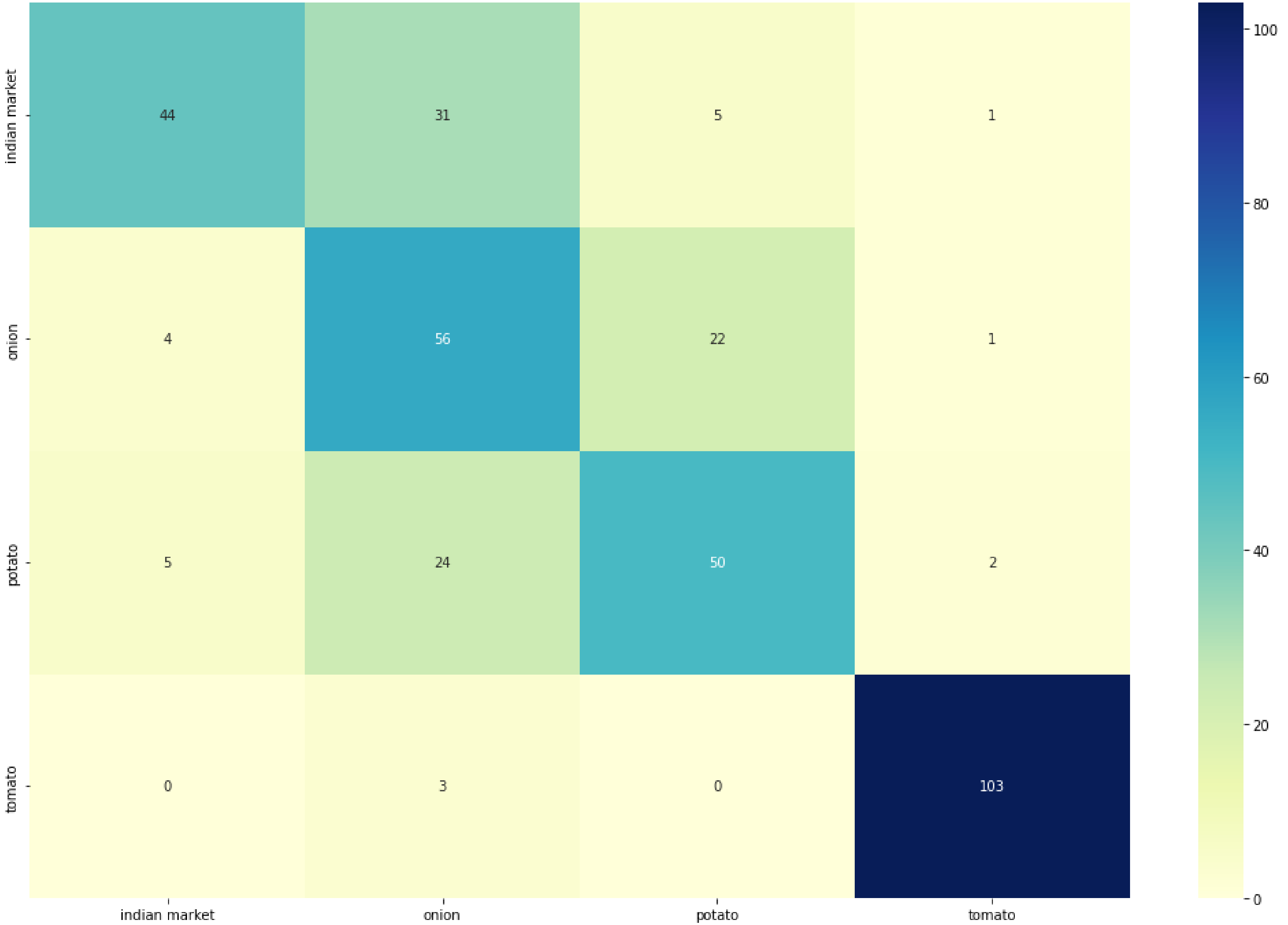


Analyze Result on Test Dataset:

In [33]:
```
def print_accuracy_stats(model, ds, class_names):
    model.load_weights("./tmp/checkpoint")
    true_onehot = tf.concat([y for x, y in ds], axis=0)
    true_categories = tf.argmax(true_onehot, axis=1)
    y_pred = model.predict(ds)
    predicted_categories = tf.argmax(y_pred, axis=1)
    test_acc = metrics.accuracy_score(true_categories, predicted_categories) * 100
    print(f'\nTest Accuracy: {test_acc:.2f}%\n')


# Note: This doesn't work with shuffled datasets
def plot_confusion_matrix(model, ds, class_names):
    model.load_weights("./tmp/checkpoint")
    true_onehot = tf.concat([y for x, y in ds], axis=0)
    true_categories = tf.argmax(true_onehot, axis=1)
    y_pred = model.predict(ds)
    predicted_categories = tf.argmax(y_pred, axis=1)
    cm = metrics.confusion_matrix(true_categories,predicted_categories) # last batch
    sns.heatmap(cm, annot=True, xticklabels=class_names, yticklabels=class_names, cmap="YlGnBu", fmt='g')
    plt.show()
```

In [34]:
```
print_accuracy_stats(model, test_ds, class_names)
plot_confusion_matrix(model, test_ds, class_names)
```

```
11/11 [==============================] - 2s 106ms/step

Test Accuracy: 72.08%

11/11 [==============================] - 1s 105ms/step
```


indian market
onion
potato
tomato
44
31
5
1
4
56
22
1
5
24
50
2
0
3
0
103
indian market
onion
potato
tomato
100
80
60
40
20
0

In [ ]:

Improving Baseline CNN to reduce Overfitting:

In [35]:
```
def new_arch(height=224, width=224):
    num_classes = 4
    hidden_size = 256

    model = tf.keras.Sequential(
        name="new_model",
        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.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
```

In [36]:
```
def compile_train(model, train_ds, val_ds, epochs=10, ckpt_path="./tmp/checkpoint"):
    callbacks = [
        tf.keras.callbacks.ReduceLROnPlateau(
            monitor="val_loss", factor=0.3, patience=5, min_lr=0.00001
        ),
        tf.keras.callbacks.ModelCheckpoint(ckpt_path, save_weights_only=True, monitor='val_accuracy', mode='max', save
        tf.keras.callbacks.EarlyStopping(
            monitor="val_loss", patience=10, min_delta=0.001, mode='min'
        ),
        tf.keras.callbacks.TensorBoard(log_dir='./Graph', histogram_freq=0, write_graph=True, write_images=True)
    ]
    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
```

In [37]:
```
def preprocess_v2(train_data, val_data, test_data, target_height=224, target_width=224):
    # Data Processing Stage with resizing and rescaling operations #same as before for test,val
    data_preprocess = tf.keras.Sequential(
        name="data_preprocess",
        layers=[
            layers.Resizing(target_height, target_width),
            layers.Rescaling(1.0/255),
        ]
    )
    # Data Processing Stage with resizing and rescaling operations
    data_augmentation = tf.keras.Sequential(
        name="data_augmentation",
        layers=[
            layers.Resizing(256, 256), # First resize to 256,256
            layers.RandomCrop(target_height, target_width), # Then randomly crop 224,224 region
            layers.Rescaling(1.0/255), # Finally rescale
        ]
    )
    # Perform Data Processing on the train, val, test dataset
    train_ds = train_data.map(
        lambda x, y: (data_augmentation(x), y), num_parallel_calls=tf.data.AUTOTUNE).prefetch(tf.data.AUTOTUNE)
    val_ds = val_data.map(
        lambda x, y: (data_preprocess(x), y), num_parallel_calls=tf.data.AUTOTUNE).prefetch(tf.data.AUTOTUNE)
    test_ds = test_data.map(
        lambda x, y: (data_preprocess(x), y), num_parallel_calls=tf.data.AUTOTUNE).prefetch(tf.data.AUTOTUNE)
    return train_ds, val_ds, test_ds
```

In [38]:
```
train_ds, val_ds, test_ds = preprocess_v2(train_data, val_data, test_data)
```

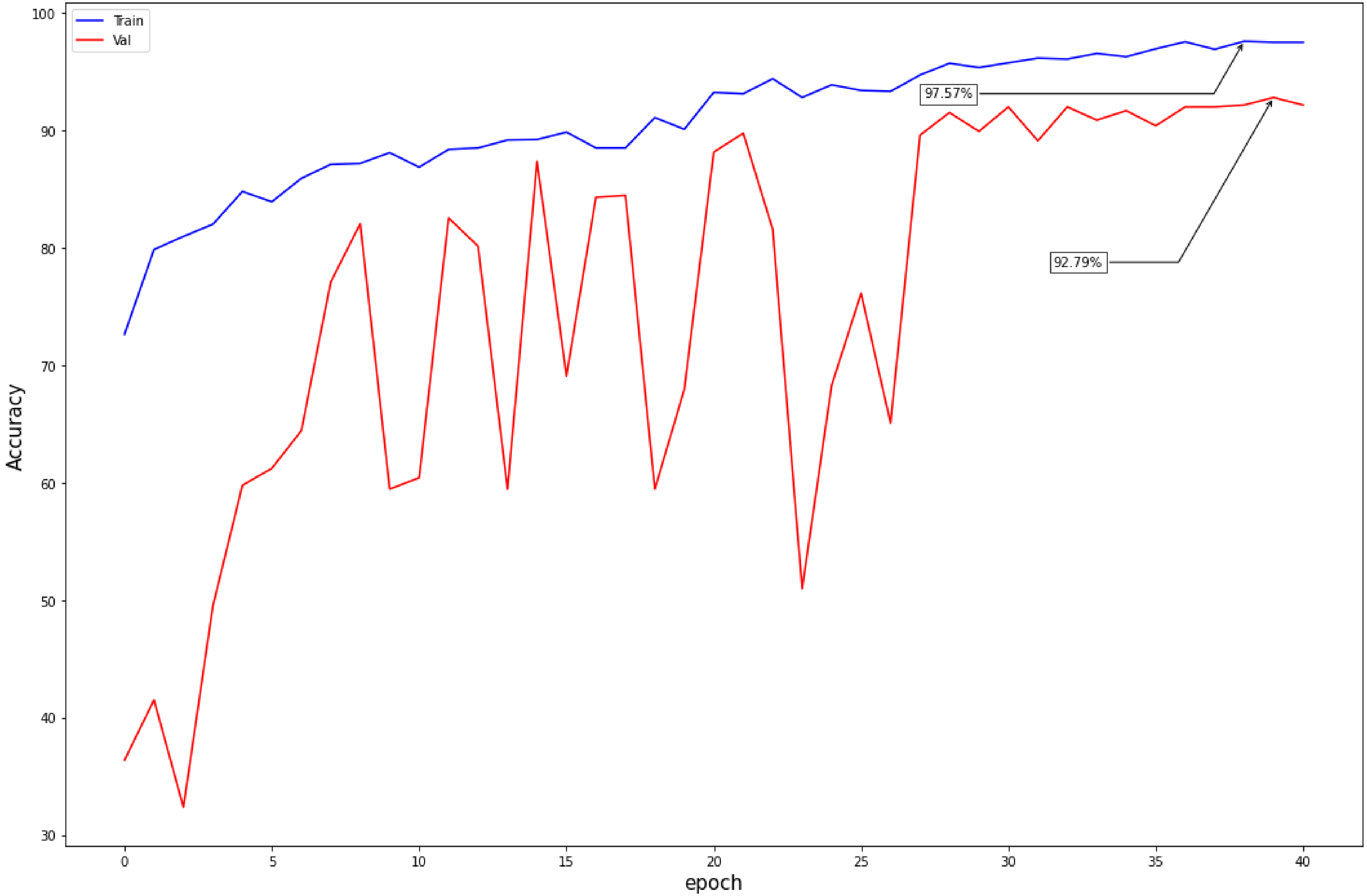
In [39]:
```
model = new_arch()
model_fit = compile_train(model, train_ds, val_ds, epochs=100)
```

```
Epoch 1/100
79/79 [==============================] - 97s 1s/step - loss: 1.3987 - accuracy: 0.7264 - val_loss: 1.9975 - val_accu
racy: 0.3638 - lr: 0.0010
Epoch 2/100
79/79 [==============================] - 87s 1s/step - loss: 1.1510 - accuracy: 0.7985 - val_loss: 1.8551 - val_accu
racy: 0.4151 - lr: 0.0010
Epoch 3/100
79/79 [==============================] - 87s 1s/step - loss: 1.0921 - accuracy: 0.8096 - val_loss: 2.3947 - val_accu
racy: 0.3237 - lr: 0.0010
Epoch 4/100
79/79 [==============================] - 89s 1s/step - loss: 0.9930 - accuracy: 0.8200 - val_loss: 1.8593 - val_accu
racy: 0.4952 - lr: 0.0010
Epoch 5/100
79/79 [==============================] - 95s 1s/step - loss: 0.8757 - accuracy: 0.8479 - val_loss: 1.5402 - val_accu
racy: 0.5978 - lr: 0.0010
Epoch 6/100
79/79 [==============================] - 97s 1s/step - loss: 0.8849 - accuracy: 0.8391 - val_loss: 1.7156 - val_accu
racy: 0.6122 - lr: 0.0010
Epoch 7/100
79/79 [==============================] - 108s 1s/step - loss: 0.8060 - accuracy: 0.8590 - val_loss: 1.6526 - val_acc
uracy: 0.6442 - lr: 0.0010
Epoch 8/100
79/79 [==============================] - 109s 1s/step - loss: 0.7742 - accuracy: 0.8710 - val_loss: 1.0570 - val_acc
uracy: 0.7708 - lr: 0.0010
Epoch 9/100
79/79 [==============================] - 96s 1s/step - loss: 0.7418 - accuracy: 0.8718 - val_loss: 0.8708 - val_accu
racy: 0.8205 - lr: 0.0010
Epoch 10/100
79/79 [==============================] - 97s 1s/step - loss: 0.6840 - accuracy: 0.8809 - val_loss: 1.3426 - val_accu
racy: 0.5946 - lr: 0.0010
Epoch 11/100
79/79 [==============================] - 95s 1s/step - loss: 0.6881 - accuracy: 0.8686 - val_loss: 1.4098 - val_accu
racy: 0.6042 - lr: 0.0010
Epoch 12/100
79/79 [==============================] - 95s 1s/step - loss: 0.6369 - accuracy: 0.8837 - val_loss: 0.7770 - val_accu
racy: 0.8253 - lr: 0.0010
Epoch 13/100
79/79 [==============================] - 94s 1s/step - loss: 0.5957 - accuracy: 0.8849 - val_loss: 1.0441 - val_accu
racy: 0.8013 - lr: 0.0010
Epoch 14/100
79/79 [==============================] - 96s 1s/step - loss: 0.5683 - accuracy: 0.8917 - val_loss: 1.3526 - val_accu
```

```
racy: 0.5946 - lr: 0.0010
Epoch 15/100
79/79 [==============================] - 95s 1s/step - loss: 0.5541 - accuracy: 0.8921 - val_loss: 0.6222 - val_accu
racy: 0.8734 - lr: 0.0010
Epoch 16/100
79/79 [==============================] - 96s 1s/step - loss: 0.5437 - accuracy: 0.8984 - val_loss: 1.4758 - val_accu
racy: 0.6907 - lr: 0.0010
Epoch 17/100
79/79 [==============================] - 95s 1s/step - loss: 0.5382 - accuracy: 0.8849 - val_loss: 0.7682 - val_accu
racy: 0.8429 - lr: 0.0010
Epoch 18/100
79/79 [==============================] - 94s 1s/step - loss: 0.5247 - accuracy: 0.8849 - val_loss: 0.6419 - val_accu
racy: 0.8446 - lr: 0.0010
Epoch 19/100
79/79 [==============================] - 95s 1s/step - loss: 0.4526 - accuracy: 0.9108 - val_loss: 1.7415 - val_accu
racy: 0.5946 - lr: 0.0010
Epoch 20/100
79/79 [==============================] - 95s 1s/step - loss: 0.4611 - accuracy: 0.9008 - val_loss: 1.7795 - val_accu
racy: 0.6795 - lr: 0.0010
Epoch 21/100
79/79 [==============================] - 95s 1s/step - loss: 0.3780 - accuracy: 0.9323 - val_loss: 0.5051 - val_accu
racy: 0.8814 - lr: 3.0000e-04
Epoch 22/100
79/79 [==============================] - 94s 1s/step - loss: 0.3739 - accuracy: 0.9311 - val_loss: 0.4647 - val_accu
racy: 0.8974 - lr: 3.0000e-04
Epoch 23/100
79/79 [==============================] - 95s 1s/step - loss: 0.3317 - accuracy: 0.9438 - val_loss: 0.6197 - val_accu
racy: 0.8157 - lr: 3.0000e-04
Epoch 24/100
79/79 [==============================] - 94s 1s/step - loss: 0.3540 - accuracy: 0.9279 - val_loss: 2.5666 - val_accu
racy: 0.5096 - lr: 3.0000e-04
Epoch 25/100
79/79 [==============================] - 94s 1s/step - loss: 0.3374 - accuracy: 0.9387 - val_loss: 1.4389 - val_accu
racy: 0.6827 - lr: 3.0000e-04
Epoch 26/100
79/79 [==============================] - 95s 1s/step - loss: 0.3444 - accuracy: 0.9339 - val_loss: 0.8404 - val_accu
racy: 0.7612 - lr: 3.0000e-04
Epoch 27/100
79/79 [==============================] - 94s 1s/step - loss: 0.3394 - accuracy: 0.9331 - val_loss: 1.7753 - val_accu
racy: 0.6506 - lr: 3.0000e-04
Epoch 28/100
79/79 [==============================] - 94s 1s/step - loss: 0.2993 - accuracy: 0.9470 - val_loss: 0.4415 - val_accu
```

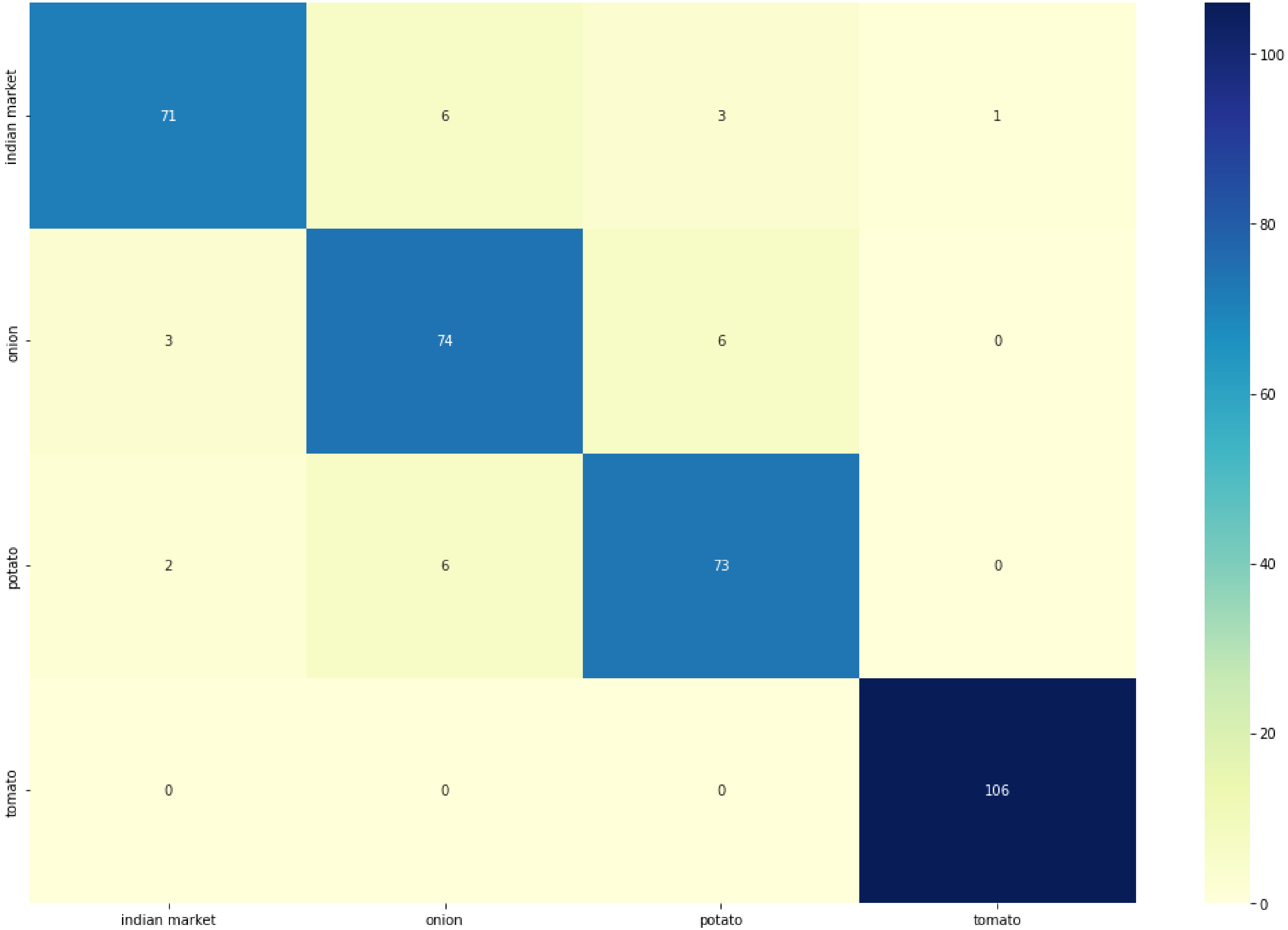
```
racy: 0.8958 - lr: 9.0000e-05
Epoch 29/100
79/79 [==============================] - 96s 1s/step - loss: 0.2876 - accuracy: 0.9570 - val_loss: 0.4039 - val_accu
racy: 0.9151 - lr: 9.0000e-05
Epoch 30/100
79/79 [==============================] - 94s 1s/step - loss: 0.2779 - accuracy: 0.9534 - val_loss: 0.4379 - val_accu
racy: 0.8990 - lr: 9.0000e-05
Epoch 31/100
79/79 [==============================] - 93s 1s/step - loss: 0.2756 - accuracy: 0.9574 - val_loss: 0.3839 - val_accu
racy: 0.9199 - lr: 9.0000e-05
Epoch 32/100
79/79 [==============================] - 95s 1s/step - loss: 0.2694 - accuracy: 0.9614 - val_loss: 0.4405 - val_accu
racy: 0.8910 - lr: 9.0000e-05
Epoch 33/100
79/79 [==============================] - 96s 1s/step - loss: 0.2577 - accuracy: 0.9606 - val_loss: 0.3948 - val_accu
racy: 0.9199 - lr: 9.0000e-05
Epoch 34/100
79/79 [==============================] - 96s 1s/step - loss: 0.2477 - accuracy: 0.9654 - val_loss: 0.4243 - val_accu
racy: 0.9087 - lr: 9.0000e-05
Epoch 35/100
79/79 [==============================] - 96s 1s/step - loss: 0.2474 - accuracy: 0.9626 - val_loss: 0.3998 - val_accu
racy: 0.9167 - lr: 9.0000e-05
Epoch 36/100
79/79 [==============================] - 94s 1s/step - loss: 0.2395 - accuracy: 0.9693 - val_loss: 0.4346 - val_accu
racy: 0.9038 - lr: 9.0000e-05
Epoch 37/100
79/79 [==============================] - 94s 1s/step - loss: 0.2212 - accuracy: 0.9753 - val_loss: 0.3971 - val_accu
racy: 0.9199 - lr: 2.7000e-05
Epoch 38/100
79/79 [==============================] - 97s 1s/step - loss: 0.2308 - accuracy: 0.9689 - val_loss: 0.4272 - val_accu
racy: 0.9199 - lr: 2.7000e-05
Epoch 39/100
79/79 [==============================] - 95s 1s/step - loss: 0.2275 - accuracy: 0.9757 - val_loss: 0.4063 - val_accu
racy: 0.9215 - lr: 2.7000e-05
Epoch 40/100
79/79 [==============================] - 96s 1s/step - loss: 0.2124 - accuracy: 0.9749 - val_loss: 0.3989 - val_accu
racy: 0.9279 - lr: 2.7000e-05
Epoch 41/100
79/79 [==============================] - 94s 1s/step - loss: 0.2170 - accuracy: 0.9749 - val_loss: 0.3972 - val_accu
racy: 0.9215 - lr: 2.7000e-05
```

In [40]:
```
plot_accuracy(model_fit)
```



In [41]:
```
print_accuracy_stats(model, test_ds, class_names)
plot_confusion_matrix(model, test_ds, class_names)
```

```
11/11 [==============================] - 3s 210ms/step

Test Accuracy: 92.31%

11/11 [==============================] - 3s 203ms/step
```


indian market
onion
potato
tomato
71
6
3
1
3
74
6
0
2
6
73
0
0
0
0
106
indian market
onion
potato
tomato
100
80
60
40
20
0

In [ ]:

Finetuning Pretrained model (MobliNetV3Large):

In [42]:
```
def preprocess_mobileNet(train_data, val_data, test_data, target_height=224, target_width=224):
    # Data Processing Stage with resizing and rescaling operations #same as before for test,val
    data_preprocess = tf.keras.Sequential(
        name="data_preprocess",
        layers=[
            layers.Resizing(target_height, target_width)
        ]
    )

    # Data Processing Stage with resizing and rescaling operations
    data_augmentation = tf.keras.Sequential(
        name="data_augmentation",
        layers=[
            layers.Resizing(256, 256), # First resize to 256,256
            layers.RandomCrop(target_height, target_width), # Then randomly crop 224,224 region
        ]
    )

    # Perform Data Processing on the train, val, test dataset
    train_ds = train_data.map(
        lambda x, y: (data_augmentation(x), y), num_parallel_calls=tf.data.AUTOTUNE).prefetch(tf.data.AUTOTUNE)
    val_ds = val_data.map(
        lambda x, y: (data_preprocess(x), y), num_parallel_calls=tf.data.AUTOTUNE).prefetch(tf.data.AUTOTUNE)
    test_ds = test_data.map(
        lambda x, y: (data_preprocess(x), y), num_parallel_calls=tf.data.AUTOTUNE).prefetch(tf.data.AUTOTUNE)

    return train_ds, val_ds, test_ds
```

In [43]:
```
def get_mobileNet_model(target_height=224, target_width=224, num_classes=4):
    pretrained_model = MobileNetV3Large(
        weights='imagenet',
        include_top=False,
        input_shape=(target_height, target_width, 3)
    )
    pretrained_model.trainable=False
    resnet_model = tf.keras.Sequential([
        pretrained_model,
        tf.keras.layers.Flatten(),
        tf.keras.layers.Dense(64, activation='relu'),
        tf.keras.layers.Dense(num_classes, activation='softmax')
    ])
    return resnet_model
```

In [44]:
```
def compile_mobileNet(model, train_ds, val_ds, epochs=10, ckpt_path="./tmp/checkpoint"):
    callbacks = [
        tf.keras.callbacks.ReduceLROnPlateau(
            monitor="val_loss", factor=0.3, patience=5, min_lr=0.00001
        ),
        tf.keras.callbacks.ModelCheckpoint(
            ckpt_path, save_weights_only=True, monitor='val_accuracy', mode='max', save_best_only=True
        ),
        tf.keras.callbacks.EarlyStopping(
            monitor="val_loss", patience=10, min_delta=0.001, mode='min'
        ),
        tf.keras.callbacks.TensorBoard(log_dir='./MobileNetGraph', histogram_freq=0, write_graph=True, write_images=Tr
    ]
    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
```

In [45]:
```
train_ds, val_ds, test_ds = preprocess_mobileNet(train_data, val_data, test_data)
```

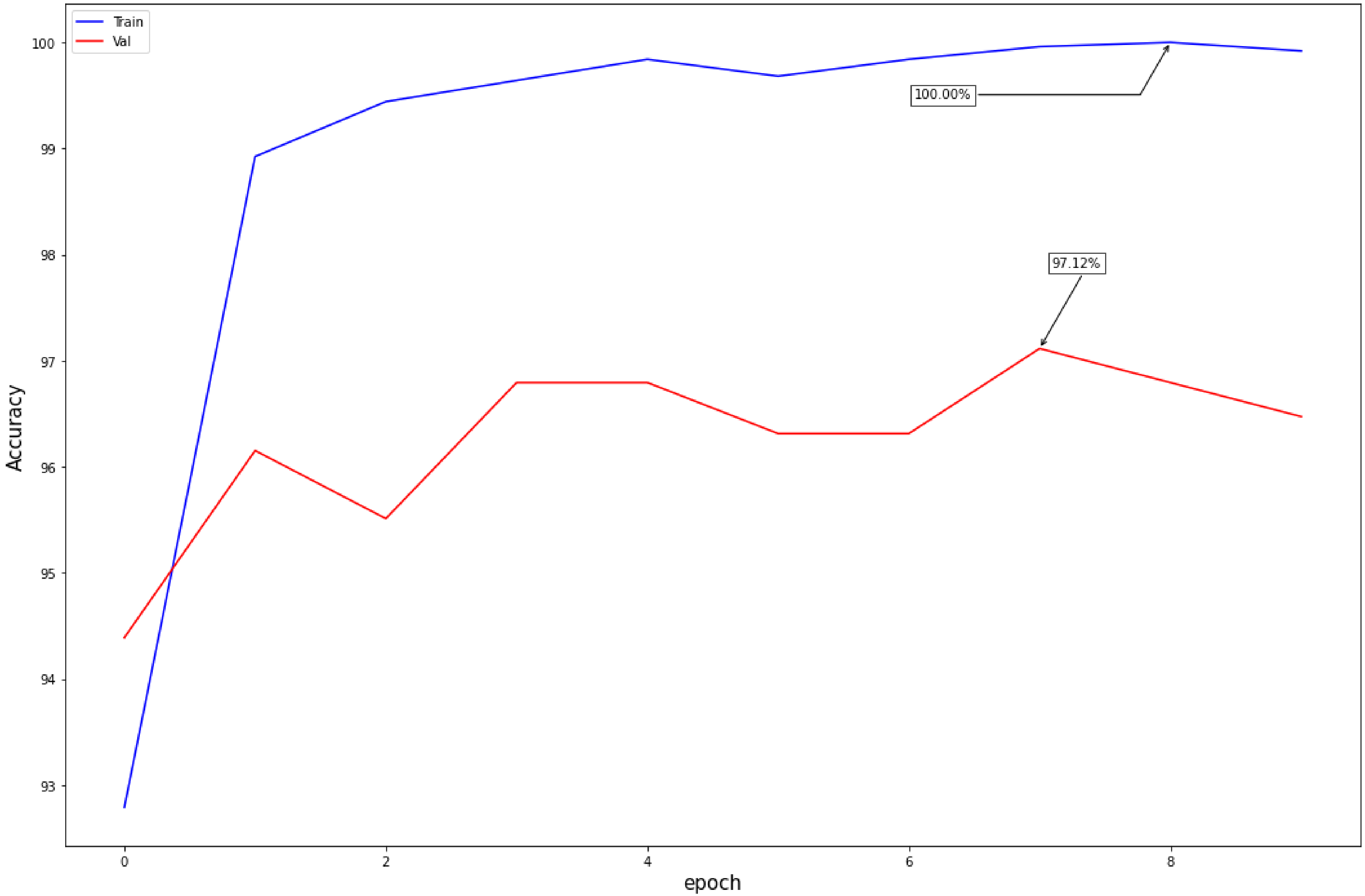
In [46]:
```
model = get_mobileNet_model()
model.summary()
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/mobilenet_v3/weights_mobilenet_v3_large_224_1.0_float_no_top_v2.h5 (https://storage.googleapis.com/tensorflow/keras-applications/mobilenet_v3/weights_mobilenet_v3_large_224_1.0_float_no_top_v2.h5)
12683000/12683000 [==============================] - 4s 0us/step
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 MobilenetV3large (Functiona  (None, 7, 7, 960)        2996352   
 l)                                                              
                                                                 
 flatten_1 (Flatten)         (None, 47040)             0         
                                                                 
 dense_4 (Dense)             (None, 64)                3010624   
                                                                 
 dense_5 (Dense)             (None, 4)                 260       
                                                                 
=================================================================
Total params: 6,007,236
Trainable params: 3,010,884
Non-trainable params: 2,996,352
_________________________________________________________________
```

In [47]:
```
model_fit = compile_mobileNet(model, train_ds, val_ds, epochs=10)
```

```
Epoch 1/10
79/79 [==============================] - 70s 835ms/step - loss: 0.4043 - accuracy: 0.9279 - val_loss: 0.1843 - val_a
ccuracy: 0.9439 - lr: 0.0010
Epoch 2/10
79/79 [==============================] - 69s 866ms/step - loss: 0.0448 - accuracy: 0.9892 - val_loss: 0.1309 - val_a
ccuracy: 0.9615 - lr: 0.0010
Epoch 3/10
79/79 [==============================] - 66s 832ms/step - loss: 0.0155 - accuracy: 0.9944 - val_loss: 0.1913 - val_a
ccuracy: 0.9551 - lr: 0.0010
Epoch 4/10
79/79 [==============================] - 67s 842ms/step - loss: 0.0078 - accuracy: 0.9964 - val_loss: 0.1384 - val_a
ccuracy: 0.9679 - lr: 0.0010
Epoch 5/10
79/79 [==============================] - 68s 850ms/step - loss: 0.0102 - accuracy: 0.9984 - val_loss: 0.1468 - val_a
ccuracy: 0.9679 - lr: 0.0010
Epoch 6/10
79/79 [==============================] - 66s 833ms/step - loss: 0.0187 - accuracy: 0.9968 - val_loss: 0.1780 - val_a
ccuracy: 0.9631 - lr: 0.0010
Epoch 7/10
79/79 [==============================] - 67s 845ms/step - loss: 0.0208 - accuracy: 0.9984 - val_loss: 0.1675 - val_a
ccuracy: 0.9631 - lr: 0.0010
Epoch 8/10
79/79 [==============================] - 71s 890ms/step - loss: 0.0011 - accuracy: 0.9996 - val_loss: 0.1462 - val_a
ccuracy: 0.9712 - lr: 3.0000e-04
Epoch 9/10
79/79 [==============================] - 71s 897ms/step - loss: 4.2666e-04 - accuracy: 1.0000 - val_loss: 0.1569 - v
al_accuracy: 0.9679 - lr: 3.0000e-04
Epoch 10/10
79/79 [==============================] - 71s 896ms/step - loss: 8.4588e-04 - accuracy: 0.9992 - val_loss: 0.1586 - v
al_accuracy: 0.9647 - lr: 3.0000e-04
```

In [48]:
```
plot_accuracy(model_fit)
```



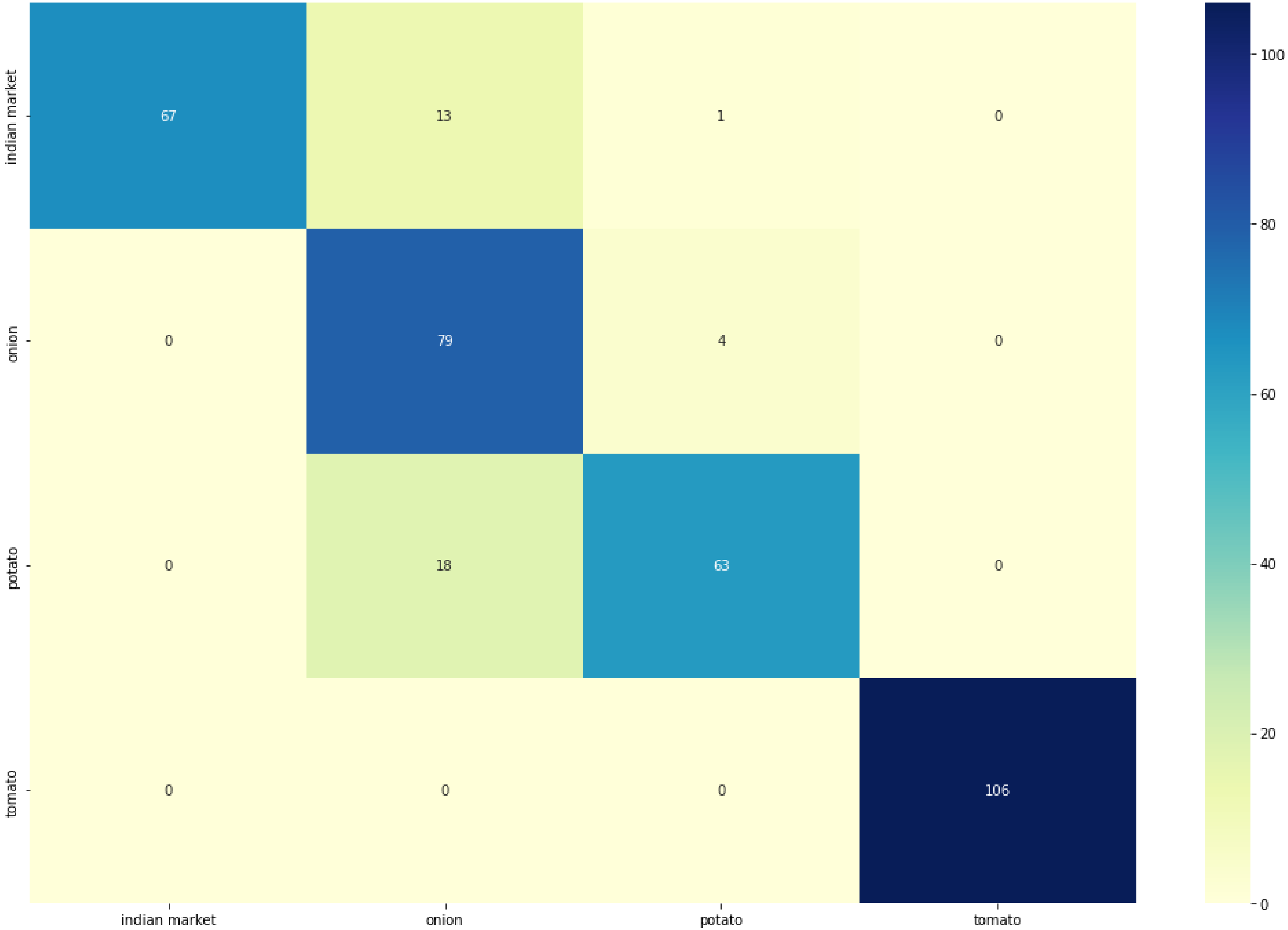
Model finetuned on MobileNet is the best model we've got so far with a validation accuracy close to 97.12%

In [ ]:

Testing Best Model:

In [49]:
```
print_accuracy_stats(model, test_ds, class_names)
plot_confusion_matrix(model, test_ds, class_names)
```

```
11/11 [==============================] - 7s 566ms/step

Test Accuracy: 89.74%

11/11 [==============================] - 7s 619ms/step
```

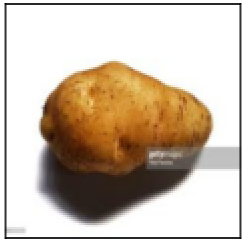

indian market
onion
potato
tomato
67
13
1
0
0
79
4
0
0
18
63
0
0
0
0
106
indian market
onion
potato
tomato
100
80
60
40
20
0

Testing accuracy is also close to 90%

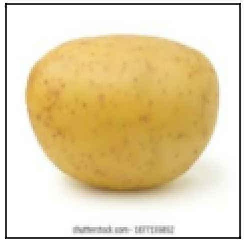
In [50]:
```
def plot_image(pred_array, true_categories, img):
    plt.grid(False)
    plt.xticks([])
    plt.yticks([])

    plt.imshow(img/255.0)

    predicted_label = np.argmax(pred_array)
    true_label = np.argmax(true_categories)

    if predicted_label == true_label:
        color = 'blue'
    else:
        color = 'red'

    plt.xlabel("{} {:2.0f}% ".format(
        class_names[predicted_label],
        100*np.max(pred_array)
        ),
        color=color
    )
```

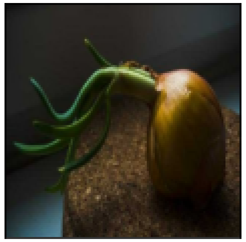
In [53]:
```
true_categories = tf.concat([y for x, y in test_ds], axis=0)
images = tf.concat([x for x, y in test_ds], axis=0)
y_pred = model.predict(test_ds)
class_names = test_data.class_names

# Randomly sample 15 test images and plot it with their predicted labels, and the true labels.
indices = random.sample(range(len(images)), 15)
# Color correct predictions in blue and incorrect predictions in red.
num_rows = 5
num_cols = 3
num_images = num_rows*num_cols
plt.figure(figsize=(4*num_cols, 2*num_rows))
for i,index in enumerate(indices):
    plt.subplot(num_rows, num_cols, i+1)
    plot_image(y_pred[index], true_categories[index], images[index])

plt.tight_layout()
plt.show()
```

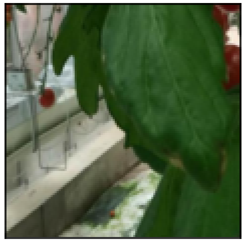
```
11/11 [==============================] - 6s 535ms/step
```


potato 100%

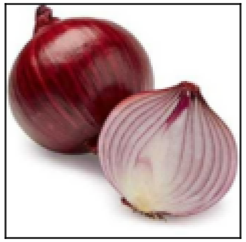

indian market 100%


potato 100%

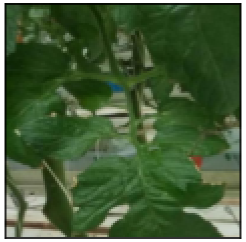

onion 100%


tomato 100%

onion 100%


onion 100%

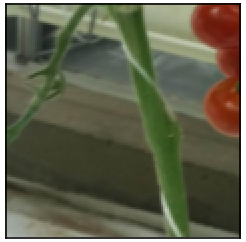

onion 100%

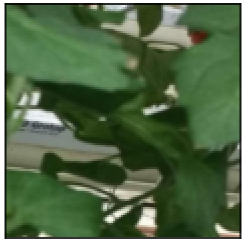

tomato 100%

indian market 99%


onion 100%


onion 100%


tomato 100%


tomato 100%


onion 95%

In [ ]:

Conclusion and Insights:

1. The model fine-tuned on the pre-trained MobileNetV3Large emerged as the most successful, achieving a near 90% test accuracy.
2. This success was largely due to the similarity between our training dataset of Indian vegetables and the "Imagenet" dataset, enabling efficient fine-tuning within 10 epochs.
3. However, the model encountered difficulty differentiating between some classes, particularly confusing potatoes for onions. This represents a primary area for improvement.
4. In short, the MobileNetV3Large model demonstrated promising results, with future work aimed at addressing classification issues and further enhancing performance.

In [ ]: