rice-image-classification-cnn

October 14, 2024

0.1 MACHINE LEARNING ASSIGNMENT 07

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LY - 7th SEMESTER

STATEMENT:
IMPLEMENT CNN MACHINE LEARNING ALGORITHM

[1]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import tensorflow as tf
import keras
from keras import optimizers , callbacks
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D , MaxPooling2D , Dense , Flatten ,␣
↪Dropout , BatchNormalization
from tabulate import tabulate
from sklearn.metrics import confusion_matrix, classification_report ,␣
↪ConfusionMatrixDisplay
import time
import random
import warnings
warnings.filterwarnings("ignore")
import os
os.environ["PYTHONWARNINGS"] = "ignore"
```

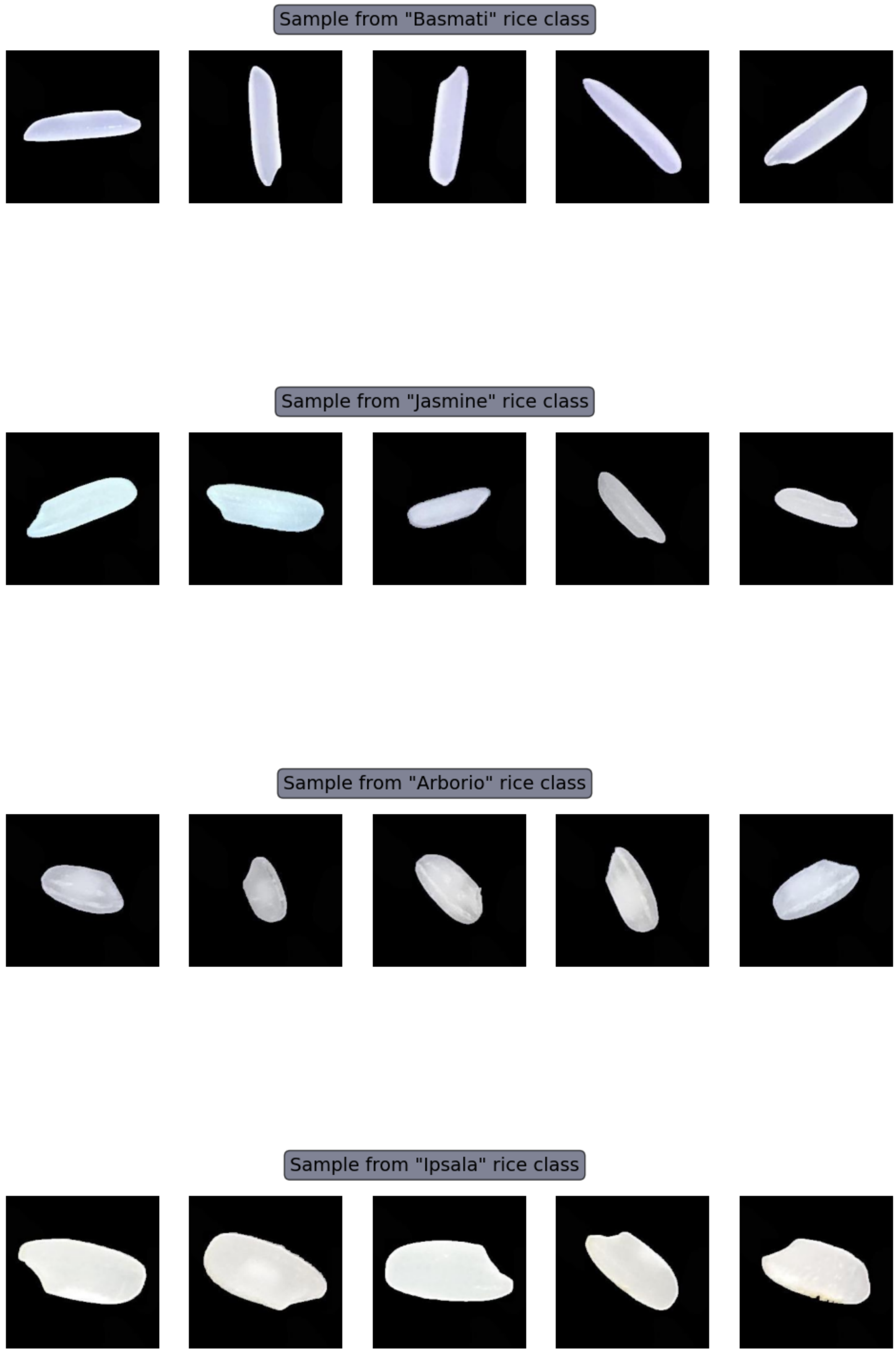
[2]:
```python
dir_ = '/kaggle/input/rice-image-dataset/Rice_Image_Dataset' # Path of folders
os.listdir(dir_) # This code gives us the list of files in our path(aka classes)
```

[2]:
```
['Karacadag',
 'Basmati',
 'Jasmine',
 'Rice_Citation_Request.txt',
 'Arborio',
 'Ipsala']
```

[3]:
```python
Classes = os.listdir(dir_) # So with this code we can store the name of classes
Classes.remove('Rice_Citation_Request.txt') # Removing the redundant file
Classes
```

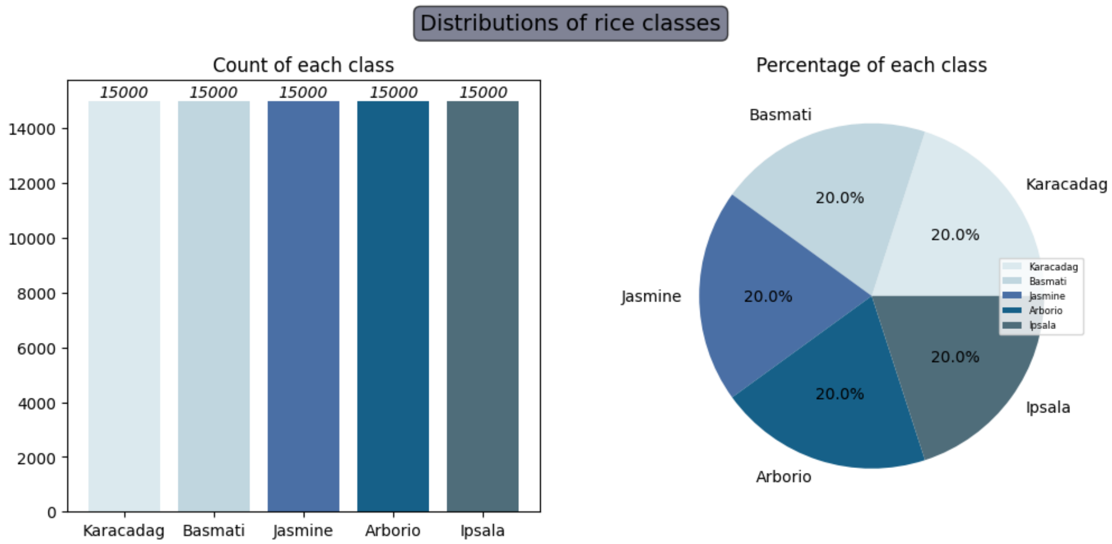
[3]: ['Karacadag', 'Basmati', 'Jasmine', 'Arborio', 'Ipsala']

[4]:
```python
# Plotting random images of each file(class)

for rice_class in Classes : # Loop through each class

    # Accessing images in files
    class_dir = os.path.join(dir_ , rice_class) # The image path of the rice␣
↪class
    images_path = os.listdir(class_dir) # List of images
    random_images = random.sample(images_path , k = 5) # Random sample of images

    # Plotting some sample images
    fig , ax = plt.subplots(1 , 5 , figsize = (12 , 3))
    plt.suptitle(f'Sample from "{rice_class}" rice class', fontsize = 14
                 , bbox=dict(facecolor='#4a4e69', alpha=0.7 ,␣
↪boxstyle='round,pad=0.3') , y = 0.9) # Title for each sample

    for i , random_image in enumerate(random_images) : # Loop for each image
        image_path = os.path.join(class_dir , random_image) # Creating image␣
↪path
        image = tf.keras.utils.load_img(image_path) # Load image

        ax[i].imshow(image) # Plot image
        ax[i].axis('off') # Remove the axis

    plt.subplots_adjust( hspace = -0.2 )
    plt.show()
    print('\n')
```


Sample from "Basmati" rice class
Sample from "Jasmine" rice class
Sample from "Arborio" rice class
Sample from "Ipsala" rice class

[5]:

```
class_count = [] # Storing the amount of data in each class

for rice_class in Classes :
    image_dir = os.path.join(dir_ , rice_class)
    image_path = os.listdir(image_dir)
    count = len(image_path) # Amount of data in each class
    class_count.append(count)


color=['#dbe9ee' , '#c0d6df','#4a6fa5' , '#166088' , '#4f6d7a' ]
fig , ax = plt.subplots(1 , 2 , figsize = (12 , 5))
plt.suptitle(f'Distributions of rice classes' , fontsize = 14
                , bbox=dict(facecolor='#4a4e69', alpha=0.7 ,␣
 ↪boxstyle='round,pad=0.3') , y = 1)

# Bar Plot
ax[0].set_title("Count of each class")
ax[0].bar(Classes , class_count , color = color) # Creating a bar plot
for i , v in enumerate(class_count):
        ax[0].text(i , v , str(v) , ha='center', va='bottom', fontstyle =␣
 ↪"oblique" , fontsize=10) # Putting each bar number on the top

# Pie plot for percentage
ax[1].set_title('Percentage of each class')
ax[1].pie(class_count,
    labels = Classes , autopct='%1.1f%%' , colors = color)
ax[1].legend(fontsize = 6 , loc = 'center right')

plt.show()
```



[6]:
```
# Loading images through keras pipeline
data = tf.keras.utils.image_dataset_from_directory(dir_ ,
                                                   image_size = (224 , 224) ,
                                                   batch_size = 32 ,
                                                   label_mode = 'categorical')␣
 ↪# for 'categorical_crossentropy' loss
```

Found 75000 files belonging to 5 classes.

[7]:
```
scaled_data = data.map(lambda x,y: (x/255 , y)) # Normalizing data
```

[8]:
```
total_batch = len(scaled_data) # Amount of total batches
print(total_batch)
```

2344

[9]:
```
train_size = int(total_batch*.7)+1 # Here we want allocate 70 percent of our␣
 ↪data set to train
val_size = int(total_batch*.2)+1
test_size = int(total_batch*.1)
print(train_size + val_size + test_size)
```

2344

[10]:
```
train = scaled_data.take(train_size) # Taking batches as the amount of trains␣
 ↪size
val = scaled_data.skip(train_size).take(val_size) # Skipping as the the amount␣
 ↪of train size and taking batches as the amount of val size
test = scaled_data.skip(train_size+val_size).take(test_size)
```

```
[11]: model = Sequential()

model.add(Conv2D(32 , (3,3) , activation = 'relu' , input_shape = (224 , 224 ,␣
 ↪3))) # We need to initialize the input shape in the first layer
model.add(BatchNormalization())
model.add(MaxPooling2D()) # Max Pooling layer to reduce the spatial dimensions␣
 ↪of the output (downsampling)

model.add(Conv2D(64 , (3,3) , activation = 'relu'))
model.add(BatchNormalization())
model.add(Conv2D(64 , (3,3) , activation = 'relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D())

model.add(Conv2D(128 , (3,3) , activation = 'relu'))
model.add(BatchNormalization())
model.add(Conv2D(128 , (3,3) , activation = 'relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D())

model.add(Flatten())
model.add(Dense(512, activation='relu'))  # Fully connected layer with 512 units
model.add(Dropout(0.3))  # Dropout layer for regularization
model.add(Dense(5 , activation = 'softmax'))

model.compile(loss='categorical_crossentropy', optimizer = 'adam' ,␣
 ↪metrics=['accuracy'])
model.summary() # To get a summary of our data
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 222, 222, 32)	896
batch_normalization (BatchNormalization)	(None, 222, 222, 32)	128
max_pooling2d (MaxPooling2D)	(None, 111, 111, 32)	0
conv2d_1 (Conv2D)	(None, 109, 109, 64)	18,496
batch_normalization_1 (BatchNormalization)	(None, 109, 109, 64)	256
conv2d_2 (Conv2D)	(None, 107, 107, 64)	36,928

```
batch_normalization_2          (None, 107, 107, 64)              256
(BatchNormalization)

max_pooling2d_1 (MaxPooling2D)    (None, 53, 53, 64)                0

conv2d_3 (Conv2D)              (None, 51, 51, 128)            73,856

batch_normalization_3          (None, 51, 51, 128)               512
(BatchNormalization)

conv2d_4 (Conv2D)              (None, 49, 49, 128)           147,584

batch_normalization_4          (None, 49, 49, 128)               512
(BatchNormalization)

max_pooling2d_2 (MaxPooling2D)    (None, 24, 24, 128)               0

flatten (Flatten)              (None, 73728)                       0

dense (Dense)                  (None, 512)                37,749,248

dropout (Dropout)              (None, 512)                         0

dense_1 (Dense)                (None, 5)                       2,565
```

Total params: 38,031,237 (145.08 MB)

Trainable params: 38,030,405 (145.07 MB)

Non-trainable params: 832 (3.25 KB)

[12]:
```
checkpoint = keras.callbacks.ModelCheckpoint(

    filepath='model_checkpoint_epoch_{epoch:02d}.keras',  # Filepath with epoch␣
↪number in the filename
    verbose=1)  # Verbosity mode; 1 for progress messages

reduce_lr = keras.callbacks.ReduceLROnPlateau(
    monitor = 'val_loss', # Quantity to be monitored
    factor = 0.5 , # Factor by which the learning rate will be reduced
    patience = 3 , # Number of epochs with no improvement after which learning␣
↪rate will be reduced
    verbose = 1 ,
```

```
    min_delta = 0.001 , # Threshold for measuring the new optimum, to only␣
↪focus on significant changes
    min_lr = 1e-5 ) # Lower bound on the learning rate

early_stop = keras.callbacks.EarlyStopping(
    monitor='val_loss', # Quantity to be monitored
    min_delta = 0.001 , # Minimum change in the monitored quantity to qualify␣
↪as an improvement
    patience = 5 , # Number of epochs with no improvement after which training␣
↪will be stopped
    verbose = 1 ,
    start_from_epoch = 10 # Number of epochs to wait before starting to monitor␣
↪improvement
)
```

[13]:
```
start_time = time.time() # Beginning of training

history = model.fit(train, epochs = 30 , validation_data = val ,
                    callbacks = [checkpoint , reduce_lr , early_stop]) #␣
↪Fitting the model

end_time = time.time() # End of training

training_time = end_time - start_time
print(f"\nTotal training time : {(training_time//60)} minutes and␣
↪{(training_time%60):.2f} seconds")
```

```
Epoch 1/30

WARNING: All log messages before absl::InitializeLog() is called are written to
STDERR
I0000 00:00:1726283322.275099      81 service.cc:145] XLA service 0x7d409800a3c0
initialized for platform CUDA (this does not guarantee that XLA will be used).
Devices:
I0000 00:00:1726283322.275201      81 service.cc:153]   StreamExecutor device
(0): Tesla T4, Compute Capability 7.5
I0000 00:00:1726283322.275208      81 service.cc:153]   StreamExecutor device
(1): Tesla T4, Compute Capability 7.5

   1/1641            7:24:51 16s/step -
accuracy: 0.2500 - loss: 2.7428

I0000 00:00:1726283334.597862      81 device_compiler.h:188] Compiled cluster
using XLA!  This line is logged at most once for the lifetime of the process.

1641/1641            0s 88ms/step -
accuracy: 0.9107 - loss: 1.6026
Epoch 1: saving model to model_checkpoint_epoch_01.keras
1641/1641            209s 117ms/step
```

```
- accuracy: 0.9107 - loss: 1.6020 - val_accuracy: 0.8097 - val_loss: 4.6538 -
learning_rate: 0.0010
Epoch 2/30
1641/1641            0s 89ms/step -
accuracy: 0.9567 - loss: 0.2620
Epoch 2: saving model to model_checkpoint_epoch_02.keras
1641/1641            184s 112ms/step
- accuracy: 0.9567 - loss: 0.2619 - val_accuracy: 0.9653 - val_loss: 0.1349 -
learning_rate: 0.0010
Epoch 3/30
1641/1641            0s 90ms/step -
accuracy: 0.9710 - loss: 0.1277
Epoch 3: saving model to model_checkpoint_epoch_03.keras
1641/1641            186s 113ms/step
- accuracy: 0.9710 - loss: 0.1277 - val_accuracy: 0.9460 - val_loss: 0.2530 -
learning_rate: 0.0010
Epoch 4/30
1641/1641            0s 90ms/step -
accuracy: 0.9774 - loss: 0.0960
Epoch 4: saving model to model_checkpoint_epoch_04.keras
1641/1641            185s 113ms/step
- accuracy: 0.9774 - loss: 0.0960 - val_accuracy: 0.1996 - val_loss: 1550.2744 -
learning_rate: 0.0010
Epoch 5/30
1641/1641            0s 89ms/step -
accuracy: 0.9794 - loss: 0.0842
Epoch 5: saving model to model_checkpoint_epoch_05.keras

Epoch 5: ReduceLROnPlateau reducing learning rate to 0.0005000000237487257.
1641/1641            185s 113ms/step
- accuracy: 0.9794 - loss: 0.0842 - val_accuracy: 0.2012 - val_loss: 1671.9143 -
learning_rate: 0.0010
Epoch 6/30
1641/1641            0s 89ms/step -
accuracy: 0.9850 - loss: 0.0615
Epoch 6: saving model to model_checkpoint_epoch_06.keras
1641/1641            184s 112ms/step
- accuracy: 0.9850 - loss: 0.0615 - val_accuracy: 0.9943 - val_loss: 0.0259 -
learning_rate: 5.0000e-04
Epoch 7/30
1641/1641            0s 89ms/step -
accuracy: 0.9908 - loss: 0.0347
Epoch 7: saving model to model_checkpoint_epoch_07.keras
1641/1641            183s 112ms/step
- accuracy: 0.9908 - loss: 0.0347 - val_accuracy: 0.9676 - val_loss: 0.1285 -
learning_rate: 5.0000e-04
Epoch 8/30
1641/1641            0s 89ms/step -
```

```
accuracy: 0.9921 - loss: 0.0358
Epoch 8: saving model to model_checkpoint_epoch_08.keras
1641/1641            184s 112ms/step
- accuracy: 0.9921 - loss: 0.0358 - val_accuracy: 0.4011 - val_loss: 14.9845 -
learning_rate: 5.0000e-04
Epoch 9/30
1641/1641            0s 89ms/step -
accuracy: 0.9929 - loss: 0.0282
Epoch 9: saving model to model_checkpoint_epoch_09.keras

Epoch 9: ReduceLROnPlateau reducing learning rate to 0.0002500000118743628.
1641/1641            183s 111ms/step
- accuracy: 0.9929 - loss: 0.0282 - val_accuracy: 0.9727 - val_loss: 0.1743 -
learning_rate: 5.0000e-04
Epoch 10/30
1641/1641            0s 89ms/step -
accuracy: 0.9956 - loss: 0.0214
Epoch 10: saving model to model_checkpoint_epoch_10.keras
1641/1641            186s 113ms/step
- accuracy: 0.9956 - loss: 0.0214 - val_accuracy: 0.9975 - val_loss: 0.0118 -
learning_rate: 2.5000e-04
Epoch 11/30
1641/1641            0s 90ms/step -
accuracy: 0.9965 - loss: 0.0151
Epoch 11: saving model to model_checkpoint_epoch_11.keras
1641/1641            186s 113ms/step
- accuracy: 0.9965 - loss: 0.0151 - val_accuracy: 0.9970 - val_loss: 0.0133 -
learning_rate: 2.5000e-04
Epoch 12/30
1641/1641            0s 90ms/step -
accuracy: 0.9966 - loss: 0.0142
Epoch 12: saving model to model_checkpoint_epoch_12.keras
1641/1641            187s 114ms/step
- accuracy: 0.9966 - loss: 0.0142 - val_accuracy: 0.9965 - val_loss: 0.0175 -
learning_rate: 2.5000e-04
Epoch 13/30
1641/1641            0s 90ms/step -
accuracy: 0.9966 - loss: 0.0132
Epoch 13: saving model to model_checkpoint_epoch_13.keras

Epoch 13: ReduceLROnPlateau reducing learning rate to 0.0001250000059371814.
1641/1641            187s 114ms/step
- accuracy: 0.9966 - loss: 0.0132 - val_accuracy: 0.9978 - val_loss: 0.0111 -
learning_rate: 2.5000e-04
Epoch 14/30
1641/1641            0s 90ms/step -
accuracy: 0.9973 - loss: 0.0086
Epoch 14: saving model to model_checkpoint_epoch_14.keras
```

```
1641/1641 188s 115ms/step
- accuracy: 0.9973 - loss: 0.0086 - val_accuracy: 0.9843 - val_loss: 0.0725 -
learning_rate: 1.2500e-04
Epoch 15/30
1641/1641 0s 90ms/step -
accuracy: 0.9976 - loss: 0.0074
Epoch 15: saving model to model_checkpoint_epoch_15.keras
1641/1641 188s 115ms/step
- accuracy: 0.9976 - loss: 0.0074 - val_accuracy: 0.9989 - val_loss: 0.0077 -
learning_rate: 1.2500e-04
Epoch 16/30
1641/1641 0s 90ms/step -
accuracy: 0.9980 - loss: 0.0070
Epoch 16: saving model to model_checkpoint_epoch_16.keras
1641/1641 188s 114ms/step
- accuracy: 0.9980 - loss: 0.0070 - val_accuracy: 0.9863 - val_loss: 0.0613 -
learning_rate: 1.2500e-04
Epoch 17/30
1641/1641 0s 90ms/step -
accuracy: 0.9979 - loss: 0.0071
Epoch 17: saving model to model_checkpoint_epoch_17.keras
1641/1641 187s 114ms/step
- accuracy: 0.9979 - loss: 0.0071 - val_accuracy: 0.9985 - val_loss: 0.0117 -
learning_rate: 1.2500e-04
Epoch 18/30
1641/1641 0s 90ms/step -
accuracy: 0.9983 - loss: 0.0064
Epoch 18: saving model to model_checkpoint_epoch_18.keras

Epoch 18: ReduceLROnPlateau reducing learning rate to 6.25000029685907e-05.
1641/1641 186s 113ms/step
- accuracy: 0.9983 - loss: 0.0064 - val_accuracy: 0.9985 - val_loss: 0.0120 -
learning_rate: 1.2500e-04
Epoch 19/30
1641/1641 0s 89ms/step -
accuracy: 0.9987 - loss: 0.0049
Epoch 19: saving model to model_checkpoint_epoch_19.keras
1641/1641 186s 113ms/step
- accuracy: 0.9987 - loss: 0.0049 - val_accuracy: 0.9985 - val_loss: 0.0086 -
learning_rate: 6.2500e-05
Epoch 20/30
1641/1641 0s 89ms/step -
accuracy: 0.9985 - loss: 0.0051
Epoch 20: saving model to model_checkpoint_epoch_20.keras
1641/1641 185s 113ms/step
- accuracy: 0.9985 - loss: 0.0051 - val_accuracy: 0.9975 - val_loss: 0.0151 -
learning_rate: 6.2500e-05
Epoch 20: early stopping
```

```
Total training time : 62.0 minutes and 15.00 seconds
```

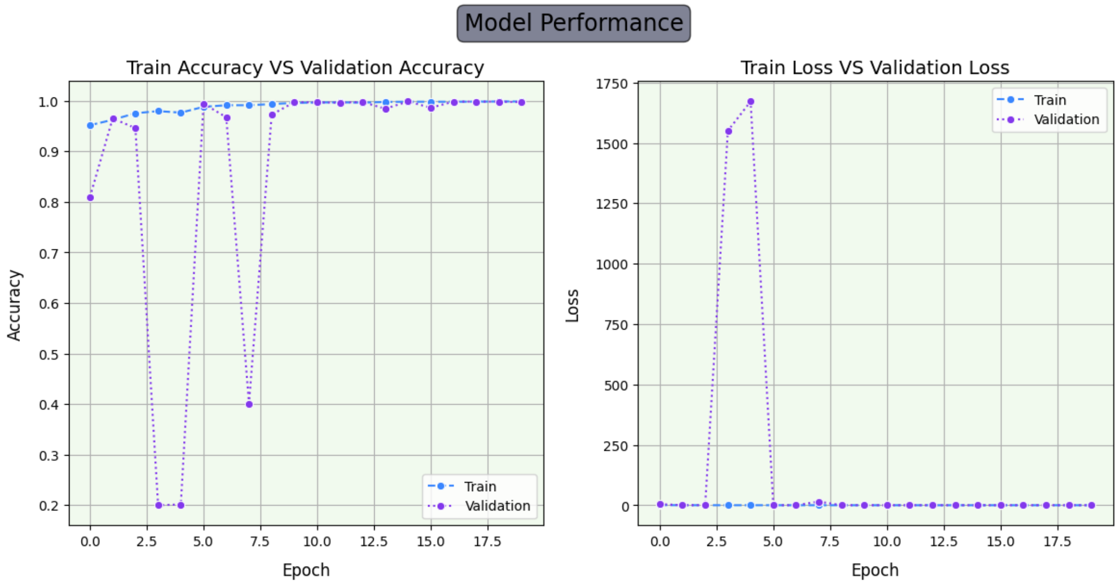
[14]:
```
# Convert result of training to a df
model_performance = pd.DataFrame(history.history)
print(tabulate(model_performance, headers='keys', tablefmt='psql'))
```

```
+----+------------+------------+----------------+---------------+---------------
--+
|    |   accuracy |       loss |   val_accuracy |      val_loss |
learning_rate |
|----+------------+------------+----------------+---------------+---------------
--|
|  0 |   0.951821 | 0.477296   |       0.809702 |    4.65378    |         0.001
|
|  1 |   0.962504 | 0.205487   |       0.965285 |    0.134878   |         0.001
|
|  2 |   0.97551  | 0.106181   |       0.946029 |    0.252987   |         0.001
|
|  3 |   0.979738 | 0.0857281  |       0.199627 | 1550.27       |         0.001
|
|  4 |   0.976672 | 0.0967933  |       0.201159 | 1671.91       |         0.001
|
|  5 |   0.988136 | 0.0434924  |       0.994336 |    0.0259087  |         0.0005
|
|  6 |   0.991335 | 0.0318718  |       0.967617 |    0.128494   |         0.0005
|
|  7 |   0.991335 | 0.0433614  |       0.401053 |   14.9845     |         0.0005
|
|  8 |   0.99364  | 0.0260081  |       0.972748 |    0.174335   |         0.0005
|
|  9 |   0.995963 | 0.0168365  |       0.997468 |    0.0118061  |         0.00025
|
| 10 |   0.996763 | 0.012849   |       0.997002 |    0.0133258  |         0.00025
|
| 11 |   0.997048 | 0.0116347  |       0.996469 |    0.0175114  |         0.00025
|
| 12 |   0.996439 | 0.0139402  |       0.997801 |    0.0111126  |         0.00025
|
| 13 |   0.997829 | 0.0076536  |       0.984342 |    0.0724951  |
0.000125 |
| 14 |   0.998324 | 0.00572639 |       0.998867 |    0.00765663 |
0.000125 |
| 15 |   0.998229 | 0.00619543 |       0.986274 |    0.0612665  |
0.000125 |
| 16 |   0.998267 | 0.00654538 |       0.998534 |    0.0117227  |
0.000125 |
| 17 |   0.998419 | 0.00577734 |       0.998534 |    0.0119839  |
```

```
0.000125 |
| 18 |   0.998781 | 0.00461791 |       0.998468 |    0.00864913 |
6.25e-05 |
| 19 |   0.998724 | 0.00426809 |       0.997468 |    0.0150798  |
6.25e-05 |
+----+------------+------------+----------------+---------------+---------------
--+
```

[15]:

```
epochs = model_performance.shape[0] # Storing the numbers of epochs

fig , ax = plt.subplots(1 , 2 , figsize = (14 , 6))
plt.suptitle(f'Model Performance' , fontsize = 17
                 , bbox=dict(facecolor='#4a4e69', alpha=0.7 ,␣
 ↪boxstyle='round,pad=0.3') , y = 1)
# Accuracy plot
ax[0].set_title("Train Accuracy VS Validation Accuracy" , fontsize = 14)
ax[0].set_ylabel("Accuracy" , fontsize = 12 , labelpad = 10)
ax[0].set_xlabel("Epoch" , fontsize = 12 , labelpad = 10)
ax[0].set_facecolor('#f1faee')
sns.lineplot(x = range(epochs) , y = model_performance['accuracy'] , label =␣
 ↪'Train' ,
             color = '#3a86ff' , marker = 'o', ls = '--' , ax = ax[0])
sns.lineplot(x = range(epochs) , y = model_performance['val_accuracy'] , label␣
 ↪= 'Validation' ,
             color = '#8338ec' , marker = 'o', ls = ':' , ax = ax[0])
ax[0].legend()
ax[0].grid()

# Loss plot
ax[1].set_title("Train Loss VS Validation Loss" , fontsize = 14)
ax[1].set_ylabel("Loss" , fontsize = 12 , labelpad = 10)
ax[1].set_xlabel("Epoch" , fontsize = 12 , labelpad = 10)
ax[1].set_facecolor('#f1faee')
sns.lineplot(x = range(epochs) , y = model_performance['loss'] , label =␣
 ↪'Train' ,
             color = '#3a86ff' , marker = 'o', ls = '--' , ax = ax[1])
sns.lineplot(x = range(epochs) , y = model_performance['val_loss'] , label =␣
 ↪'Validation' ,
             color = '#8338ec' , marker = 'o', ls = ':' , ax = ax[1])
ax[1].legend()
ax[1].grid()

plt.show()
```



[16]:
```
best_epoch = model_performance['val_loss'].idxmin() # index(epoch) of minimum␣
↪val loss

# Storing the name of the best model so we can load it
if best_epoch<10 :
    best_model_name = 'model_checkpoint_epoch_{epoch:02d}.keras'.format(epoch =␣
↪best_epoch)
else :
    best_model_name = 'model_checkpoint_epoch_{epoch:d}.keras'.format(epoch =␣
↪best_epoch)
print(f"Epoch of the best model : {best_epoch}")

# Load the optimal model saved in output folder after training
best_model = keras.models.load_model(best_model_name)

# Evaluate the model's performance on the test dataset
loss, accuracy = best_model.evaluate(test)

# Display the evaluation results with clear and formatted output
print("\nModel Evaluation Results:")
print(f'Loss: {loss:.5f}')
print(f'Accuracy: {accuracy * 100:.2f}%')
```

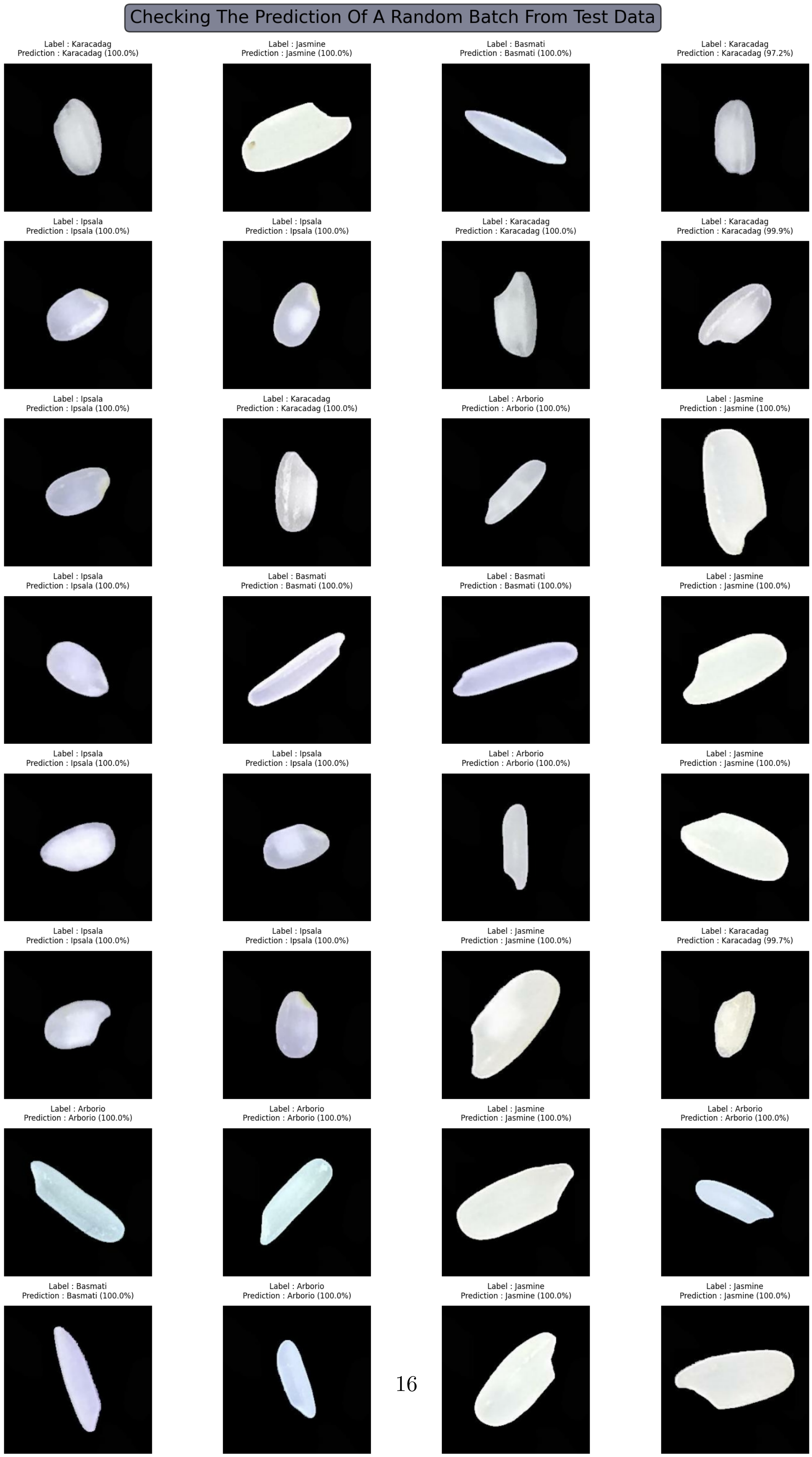
```
Epoch of the best model : 14
234/234                 50s 58ms/step -
accuracy: 0.9793 - loss: 0.1222

Model Evaluation Results:
```

```
Loss: 0.10248
Accuracy: 98.14%
```

[17]:
```
# Storing true and predicted labels of the batch

raw_test = test.map(lambda x,y: (x*255 , y)) # Re-scale back our test data so␣
↪we can show the image
test_iterator = raw_test.as_numpy_iterator() # Turn the test data into a numpy␣
↪iterator so we can take a batch from it
batch = test_iterator.next() # Take a batch

f = lambda x:x/255
temp_batch = f(batch[0])
raw_batch_predict = best_model.predict(temp_batch) # First element of the batch␣
↪stores images(X)
batch_predict = np.argmax(raw_batch_predict , axis = 1) # So we predict by␣
↪using that
batch_labels = np.argmax(batch[1] , axis = 1) # And the second element shows␣
↪the labels so we store the index of the max argument
```

```
1/1              1s 542ms/step
```

[18]:
```
# Plotting the batch

fig , ax = plt.subplots(8,4 , figsize = (12 , 20) , dpi=200)
ax = ax.flatten() # Flatten ax so we could iterate tthrough it
plt.suptitle(f'Checking The Prediction Of A Random Batch From Test Data',␣
↪fontsize = 14
                 , bbox=dict(facecolor='#4a4e69', alpha=0.7 ,␣
↪boxstyle='round,pad=0.3') , y = 0.91)

for n , i in enumerate(ax) :

    i.imshow(batch[0][n].astype(int)) # Plotting the image
    i.axis('off') # Remove the axis
    i.set_title(f"Label : {Classes[batch_labels[n]]}\n"
                f"Prediction : {Classes[batch_predict[n]]} ({100*np.
↪max(raw_batch_predict[n]):.1f}%)" ,
                fontsize = 6) # Setting true and predicted label as the title
plt.show()
```


Checking The Prediction Of A Random Batch From Test Data
Label : Karacadag
Prediction : Karacadag (100.0%)
Label : Jasmine
Prediction : Jasmine (100.0%)
Label : Basmati
Prediction : Basmati (100.0%)
Label : Karacadag
Prediction : Karacadag (97.2%)
Label : Ipsala
Prediction : Ipsala (100.0%)
Label : Ipsala
Prediction : Ipsala (100.0%)
Label : Karacadag
Prediction : Karacadag (100.0%)
Label : Karacadag
Prediction : Karacadag (99.9%)
Label : Ipsala
Prediction : Ipsala (100.0%)
Label : Karacadag
Prediction : Karacadag (100.0%)
Label : Arborio
Prediction : Arborio (100.0%)
Label : Jasmine
Prediction : Jasmine (100.0%)
Label : Ipsala
Prediction : Ipsala (100.0%)
Label : Basmati
Prediction : Basmati (100.0%)
Label : Basmati
Prediction : Basmati (100.0%)
Label : Jasmine
Prediction : Jasmine (100.0%)
Label : Ipsala
Prediction : Ipsala (100.0%)
Label : Ipsala
Prediction : Ipsala (100.0%)
Label : Arborio
Prediction : Arborio (100.0%)
Label : Jasmine
Prediction : Jasmine (100.0%)
Label : Ipsala
Prediction : Ipsala (100.0%)
Label : Ipsala
Prediction : Ipsala (100.0%)
Label : Jasmine
Prediction : Jasmine (100.0%)
Label : Karacadag
Prediction : Karacadag (99.7%)
Label : Arborio
Prediction : Arborio (100.0%)
Label : Arborio
Prediction : Arborio (100.0%)
Label : Jasmine
Prediction : Jasmine (100.0%)
Label : Arborio
Prediction : Arborio (100.0%)
Label : Basmati
Prediction : Basmati (100.0%)
Label : Arborio
Prediction : Arborio (100.0%)
Label : Jasmine
Prediction : Jasmine (100.0%)
Label : Jasmine
Prediction : Jasmine (100.0%)

[19]:
```
# Initialize a list to hold all labels of the test dataset
true_labels = []
pred_labels = []

# Iterate through the test dataset to access labels
for image , labels in test:

    y_pred_raw = best_model.predict_on_batch(image) # Predict a batch of image
    pred_labels.extend(np.argmax(y_pred_raw , axis = 1)) # Appened it to the␣
 ↪pediction list

    # Convert labels tensor to a NumPy array and extend the list
    true_labels.extend(labels.numpy())

# Convert list to a NumPy array for easier handling
true_labels = np.array(true_labels)

Y_test = np.argmax(true_labels , axis = 1)
pred_labels = np.array(pred_labels)
```

[20]:
```
# Classification report and confusion matrix

print('\33[34m' , classification_report(Y_test, pred_labels , target_names =␣
 ↪Classes))

cm_display = ConfusionMatrixDisplay(confusion_matrix(Y_test , pred_labels) ,␣
 ↪display_labels = Classes)
cm_display.plot(colorbar=False, cmap = 'PuBu')
plt.title('Confusion Matrix')
plt.show()
```

	precision	recall	f1-score	support
Karacadag	1.00	0.92	0.96	1505
Basmati	0.99	1.00	1.00	1514
Jasmine	1.00	1.00	1.00	1533
Arborio	0.99	0.99	0.99	1418
Ipsala	0.93	1.00	0.96	1510
accuracy			0.98	7480
macro avg	0.98	0.98	0.98	7480
weighted avg	0.98	0.98	0.98	7480