Assignment 6

Name: Gourav Kumar Shaw

Roll Number: 2020CSB010

Machine Learning Lab

Task 1

Download and extract the flower image dataset from https://www.kaggle.com/alxmamaev/flowers-recognition.

Task 2

The dataset contains five classes of flower images of variable sizenamely chamomile, tulip, rose, sunflower, dandelion. Resize all images to 80*80 pixels and convert all color images to grey images.

Task 3

Randomly shuffle all images to create training, test set with ratio of 90:10, respectively. (Reduce the training size by 1/ 5 if computation resources are limited).

```
import tensorflow as tf
import random


import os
os.environ["TF_CPP_MIN_LOG_LEVEL"] = "3"

DATASET_DIRECTORY_PATH = '../ML_DRIVE/Assign_6/flowers/'
seed = random.randint(0,100)

train_dataset = tf.keras.preprocessing.image_dataset_from_directory(
    directory= DATASET_DIRECTORY_PATH,
    labels="inferred",
    label_mode="categorical",
    color_mode="grayscale",
    batch_size=32,
    image_size=(80,80),
```

```
    shuffle=True,
    seed=seed,
    validation_split=0.1, #90:10 split
    subset='training',
    crop_to_aspect_ratio=False,
)

val_dataset = tf.keras.preprocessing.image_dataset_from_directory(
    directory= DATASET_DIRECTORY_PATH,
    labels="inferred",
    label_mode="categorical",
    color_mode="grayscale",
    batch_size=32,
    image_size=(80,80),
    shuffle=True,
    seed=seed,
    validation_split=0.1, #90:10 split
    subset='validation',
    crop_to_aspect_ratio=False,
)
```

```
Found 4317 files belonging to 5 classes.
Using 3886 files for training.
Found 4317 files belonging to 5 classes.
Using 431 files for validation.
```

```
train_dataset
```

```
<BatchDataset element_spec=(TensorSpec(shape=(None, 80, 80, 1), dtype=tf.float32,
name=None), TensorSpec(shape=(None, 5), dtype=tf.float32, name=None))>
```

Task 4

Train a Convolutional neural network with max pooling and a fully connected layer at the top, to classify the flower images. Now run the network by changing the following hyper-parameters:

```
input_shape = (80, 80, 1)
num_class = 5
```

```
from tensorflow.keras import Sequential
from tensorflow.keras.layers import \
    Conv2D, Dense, Input, MaxPool2D, Flatten, \
    Dropout, AvgPool2D, LeakyReLU, BatchNormalization
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.losses import CategoricalCrossentropy
import matplotlib.pyplot as plt
```

```
from tensorflow.keras.metrics import Precision, Recall
from tensorflow.math import confusion_matrix
import numpy as np
import seaborn as sns

LRELU_APLHA = 0.01


def _plot_history(
    history: 'tf.keras.callbacks.History',
    conv_kernels: 'list[tuple[int, int]]',
    conv_filters: 'list[int]',
    activation: 'str',
    pool: 'str',
    num_fc_layers: 'int'
):
    plt.figure(figsize=(12, 5))
    plt.subplot(1, 2, 1)
    plt.plot(history.history['loss'], label='Training')
    plt.plot(history.history['val_loss'], label='Validation')
    plt.ylabel('Loss')
    plt.xlabel('Epoch')
    plt.legend()
    plt.title(f'Loss vs epoch')

    plt.subplot(1, 2, 2)
    plt.plot(history.history['accuracy'], label='Training')
    plt.plot(history.history['val_accuracy'], label='Validation')
    plt.ylabel('Accuracy')
    plt.xlabel('Epoch')
    plt.legend()
    plt.title(f'Accuracy vs epoch')

    plt.suptitle(
        f'filters {conv_filters}; kernels {conv_kernels}; {pool}_pool; {activation}; dens
    plt.show()


def _plot_confusion_matrix(y_val: 'list[int]',
                           y_pred: 'list[int]'):
    matrix = confusion_matrix(y_val, y_pred)
    fig = plt.figure(figsize=(12, 5))
    sns.heatmap(
        matrix,
        xticklabels=range(1, num_class + 1),
        yticklabels=range(1, num_class + 1),
        linewidth=0.5,
        cmap='coolwarm',
        annot=True,
        cbar=True)
    plt.title('Confusion Matrix for the above model')
```

```
    plt.ylabel('Actual Value')
    plt.xlabel('Predicted Value')
    plt.show()


def train_model(
    conv_kernels: 'list[tuple[int, int]]',
    conv_filters: 'list[int]',
    activation: 'str',
    pool: 'str',
    drop_rate: 'float',
    num_fc_layers: 'int',
    train_dataset: "tf.data.Dataset",
    val_dataset: "tf.data.Dataset",
    add_batch_norm=False,
    fc_layer_size=64,
    num_epochs=100,
    extra_conv_layers=0,
    give_model=False
):

    model = Sequential()
    model.add(Input(shape=input_shape))

    for filtr, kernel in zip(conv_filters, conv_kernels):
        if activation == 'lrelu':
            model.add(Conv2D(
                filters=filtr,
                kernel_size=kernel,
                activation=LeakyReLU(alpha=LRELU_APLHA)
            ))
        else:
            model.add(Conv2D(
                filters=filtr,
                kernel_size=kernel,
                activation=activation
            ))

        if pool.lower() == 'max':
            model.add(MaxPool2D())
        elif pool.lower() == 'avg':
            model.add(AvgPool2D())
        else:
            raise Exception('argument pool is undefined')

        if add_batch_norm:
            model.add(BatchNormalization())

        if drop_rate > 0:
            model.add(Dropout(rate=drop_rate))
```

```
# add extra_conv_layers

# also padding "same" cause image dimension is reducing to 0 otherwise
for i in range(0, extra_conv_layers):
    conv_filters.append(conv_filters[-1]*2)
    conv_kernels.append(conv_kernels[-1])

    if activation == 'lrelu':
        model.add(Conv2D(
            filters=conv_filters[-1],
            kernel_size=conv_kernels[-1],
            activation=LeakyReLU(alpha=LRELU_APLHA),
            padding='same'
        ))
    else:
        model.add(Conv2D(
            filters=conv_filters[-1],
            kernel_size=conv_kernels[-1],
            activation=activation,
            padding='same'
        ))

model.add(Flatten())

for _ in range(num_fc_layers):
    if activation == 'lrelu':
        model.add(Dense(
            units=fc_layer_size,
            activation=LeakyReLU(alpha=LRELU_APLHA)
        ))
    else:
        model.add(Dense(
            units=fc_layer_size,
            activation=activation
        ))

model.add(Dense(units=num_class, activation='softmax'))

# model.summary()

model.compile(loss=CategoricalCrossentropy(),
              metrics=['accuracy', Precision(), Recall()])

callback = [
    EarlyStopping(
        monitor='val_loss',
        patience=10,
        restore_best_weights=True
    )
]
```

```
    -

    history = model.fit(x=train_dataset,
                        epochs=num_epochs,
                        verbose=0,
                        callbacks=callback if num_epochs == 100 else None,
                        validation_data=val_dataset
                        )

    val_loss, val_accuracy, val_precision, val_recall = \
        model.evaluate(val_dataset, verbose=0)

    _plot_history(
        history=history,
        conv_filters=conv_filters,
        conv_kernels=conv_kernels,
        activation=activation,
        pool=pool,
        num_fc_layers=num_fc_layers
    )

    # convert categorical to numeric for confusion matrix plotting
    y_val = [np.argmax(res) for res in np.concatenate(
        [y for x, y in val_dataset], axis=0)]
    y_predict = [np.argmax(res) for res in model.predict(val_dataset)]
    _plot_confusion_matrix(y_val, y_predict)

    if give_model:
        return val_loss, val_accuracy, val_precision, val_recall, model

    return val_loss, val_accuracy, val_precision, val_recall
```

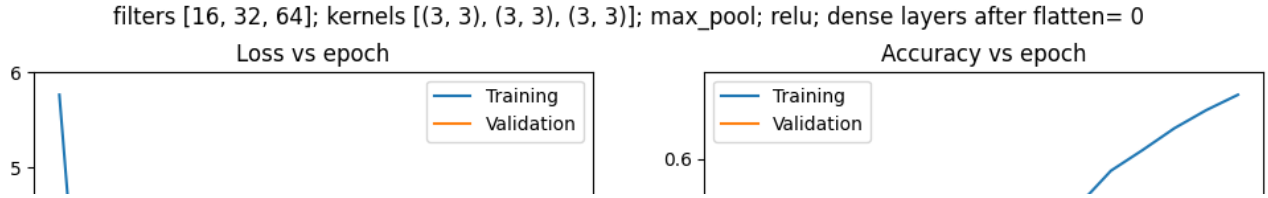
Task 4.1

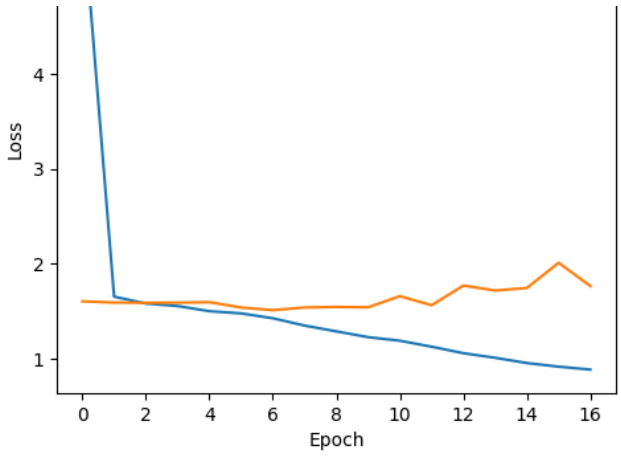
Analyze the performance of convolution window kernel size

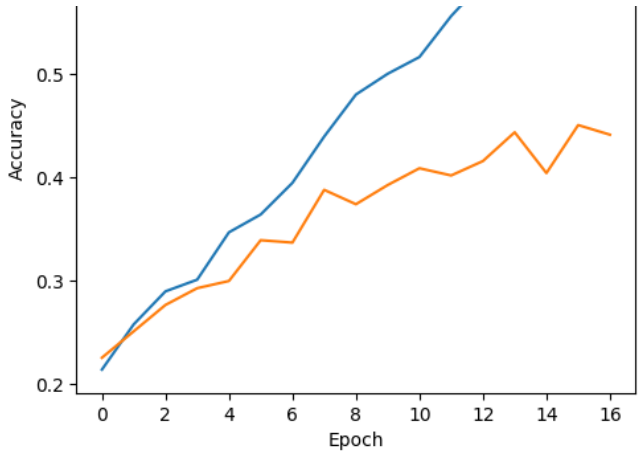
Convolution Layer	Convolution kernel_size	Convolution filters size	Pooling Layers	Activation	FC layer (after Flatten)	
3	(3*3, 3*3, 3*3)	[16,32,64]	Max_Pooling	Relu	1	
3	(3*3, 3*3, 5*5)	[16,32,64]	Max_Pooling	Relu	1	
3	(3*3, 5*5, 5*5)	[16,32,64]	Max_Pooling	Relu	1	
3	(5*5, 5*5, 5*5)	[16,32,64]	Max_Pooling	Relu	1	

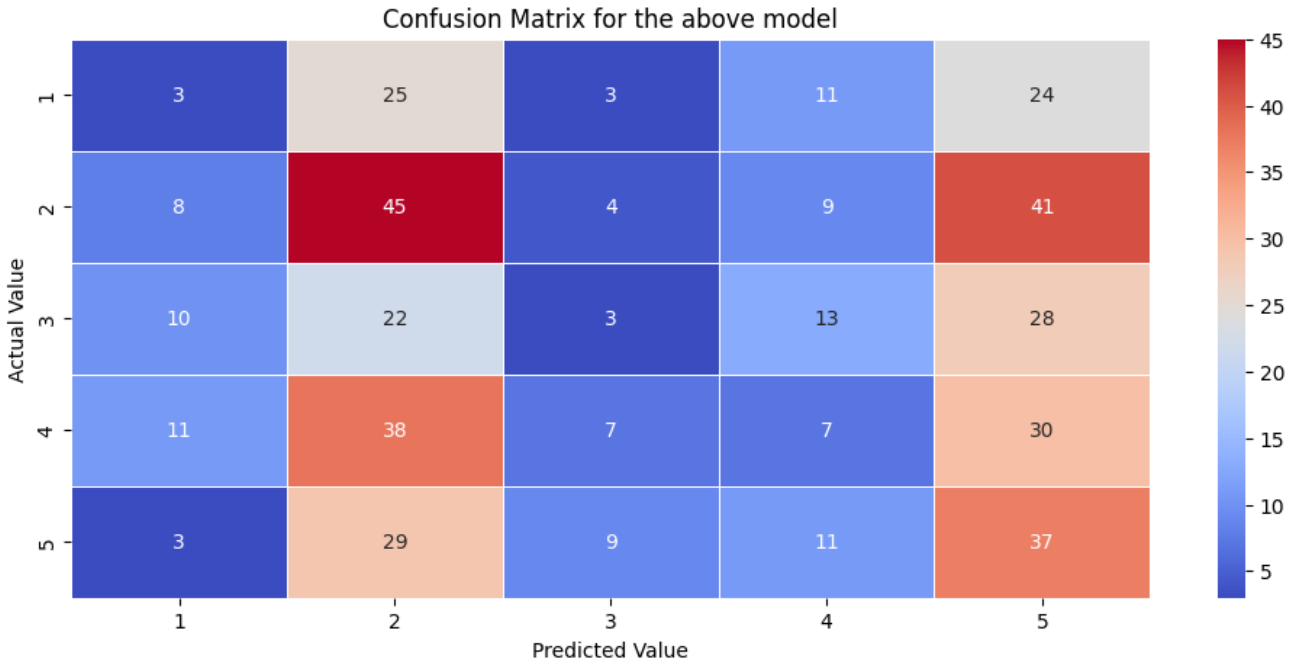
```
import pandas as pd

result = pd.DataFrame(columns=[
    'Convolution kernel_size',
    'Convolution filters size',
    'Pooling Layers',
```

```
    'Activation',
    'FC layer (after Flatten)',
    'Dropout Rate',
    'Validation Loss',
    'Validation Accuracy',
    'Validation Precision',
    'Validation Recall'
])

convolution_kernels = [
    [(3, 3), (3, 3), (3, 3)],
    [(3, 3), (3, 3), (5, 5)],
    [(3, 3), (5, 5), (5, 5)],
    [(5, 5), (5, 5), (5, 5)],
]
convolution_filters = [16, 32, 64]
activation = 'relu'
dropout_rate = 0.1
num_fc_layers = 0
pool='max'

for kernels in convolution_kernels:
    val_loss, val_acc, val_precision, val_recall = train_model(
        drop_rate=dropout_rate,
        conv_kernels=kernels,
        conv_filters=convolution_filters,
        activation=activation,
        pool=pool,
        num_fc_layers=num_fc_layers,
        train_dataset=train_dataset,
        val_dataset=val_dataset
    )

    result.loc[len(result.index)] = [
        kernels,
        convolution_filters,
        pool,
        activation,
        num_fc_layers,
        dropout_rate,
        val_loss,
        val_acc,
        val_precision,
        val_recall
    ]
```

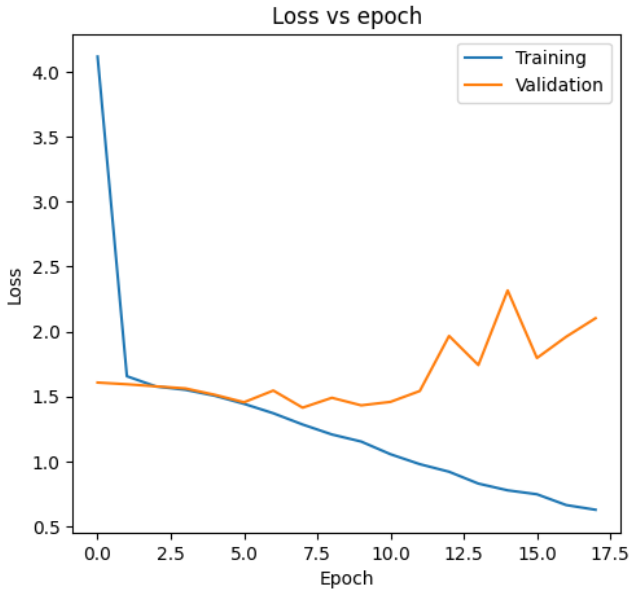


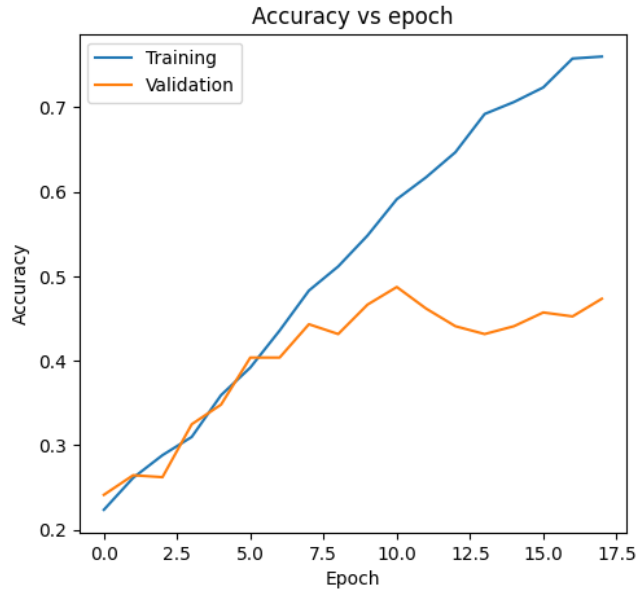


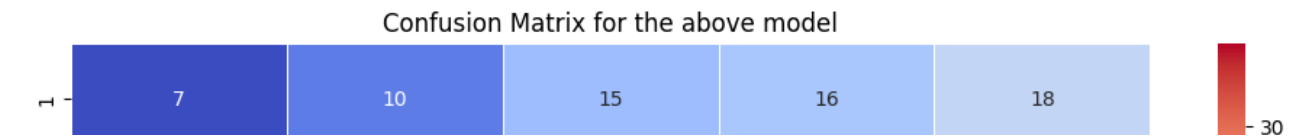


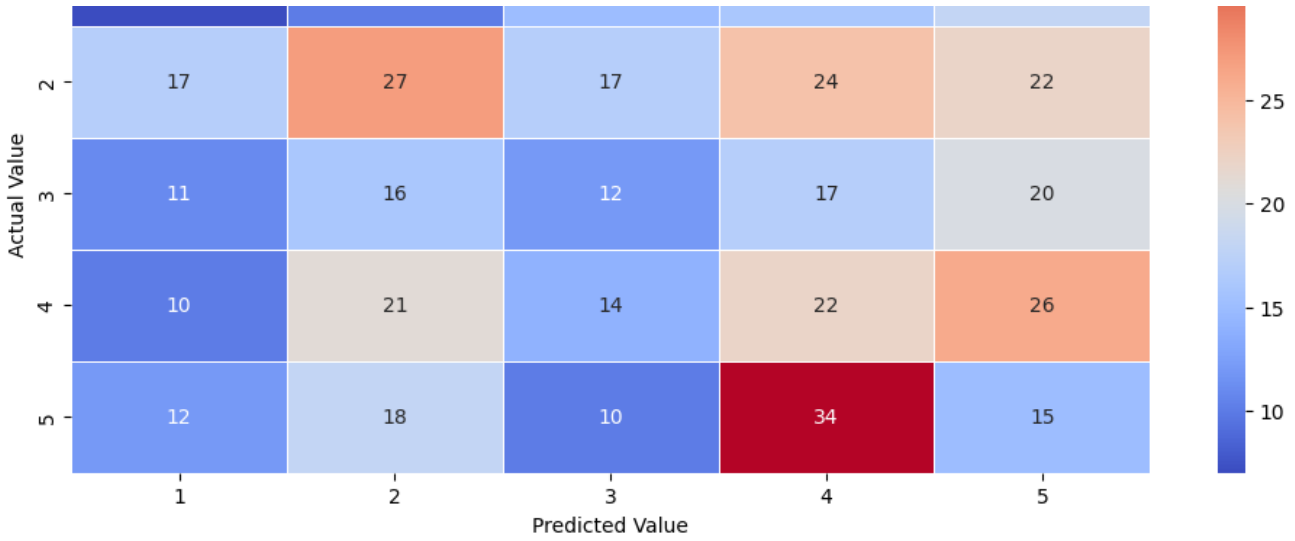


filters [16, 32, 64]; kernels [(3, 3), (3, 3), (5, 5)]; max_pool; relu; dense layers after flatten= 0

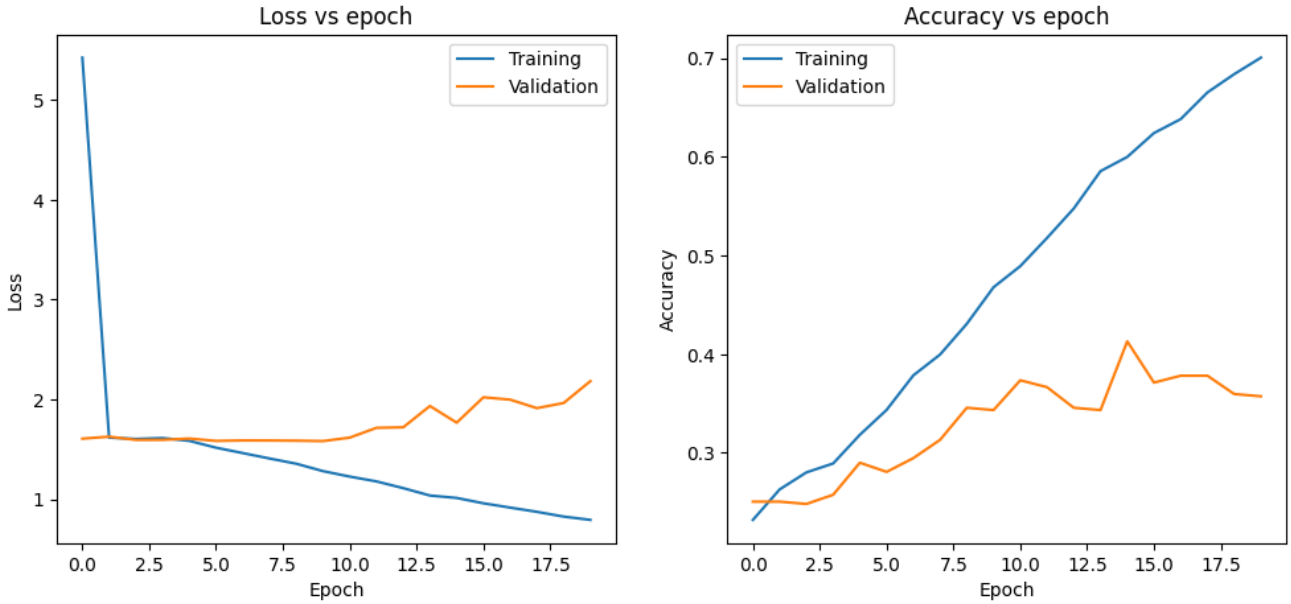


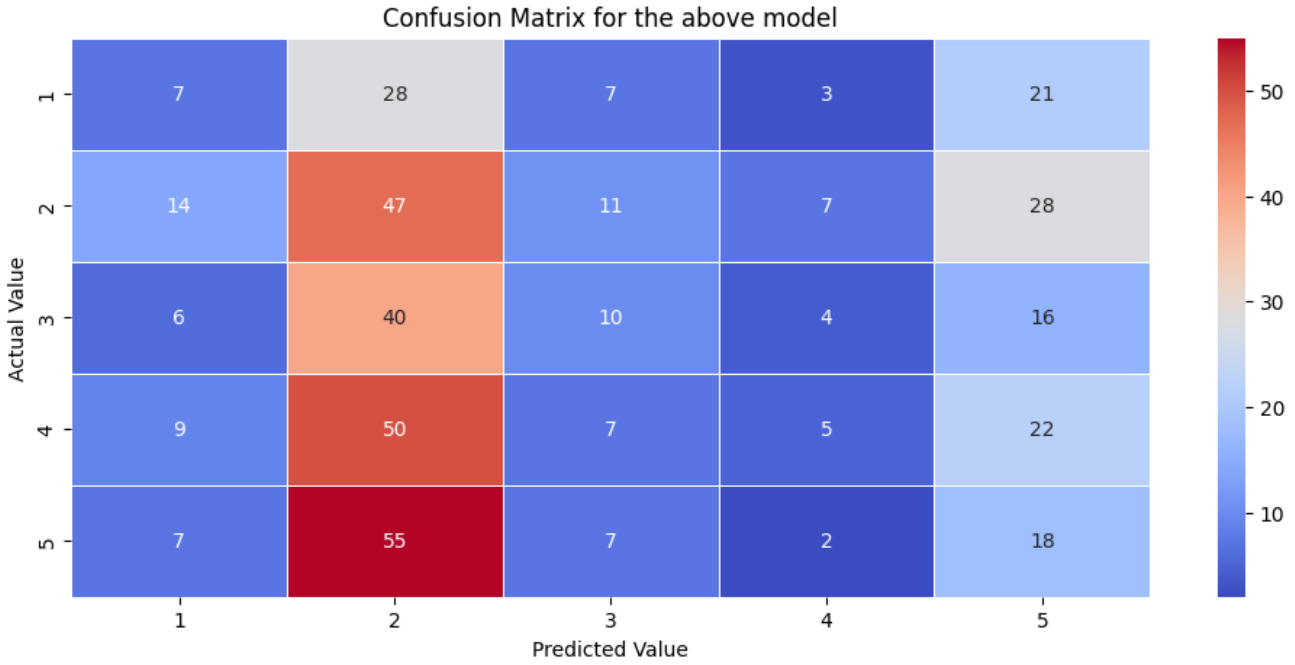




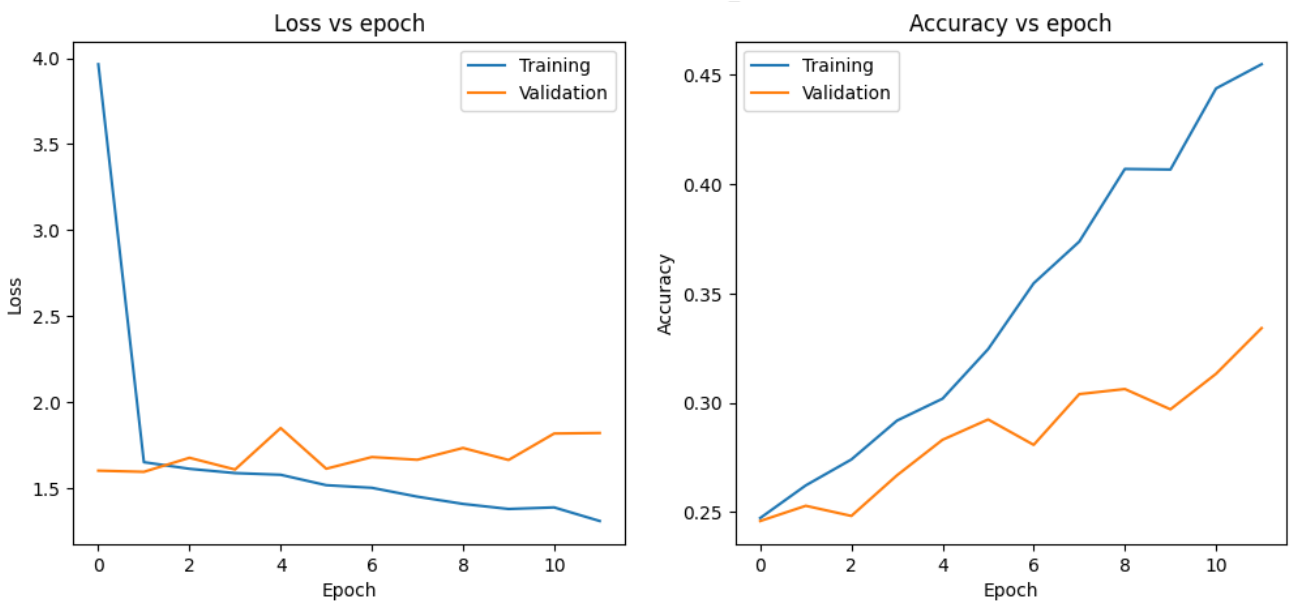


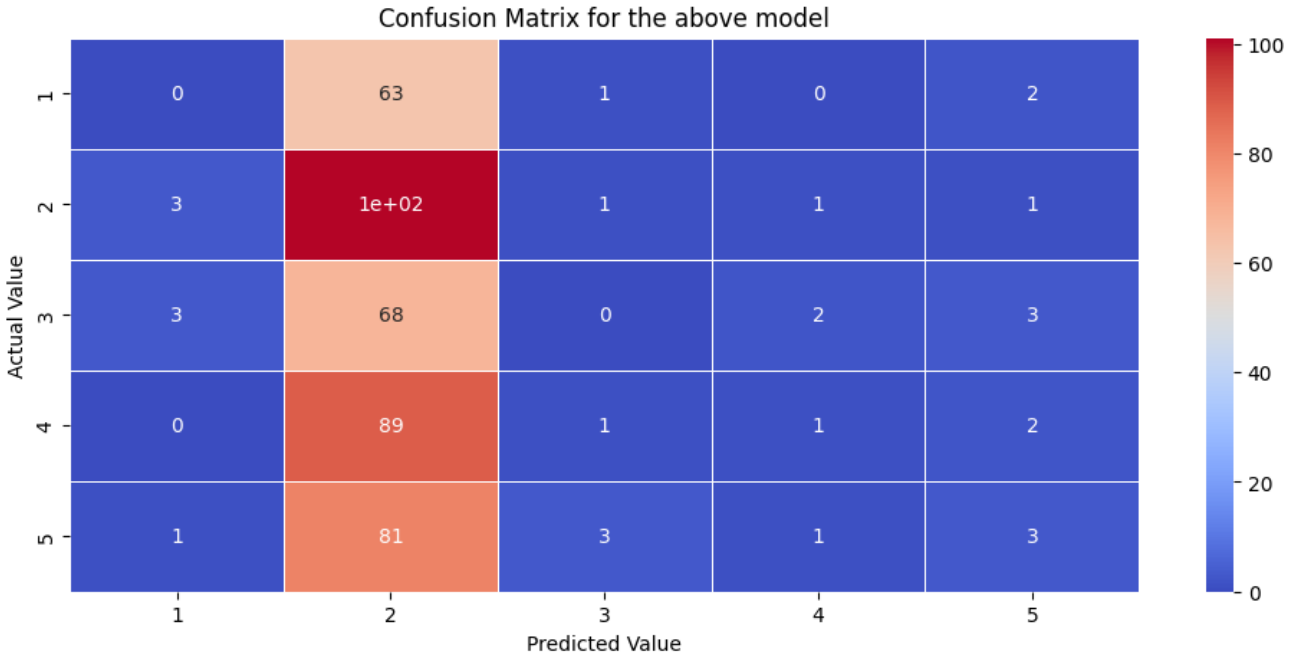
filters [16, 32, 64]; kernels [(3, 3), (5, 5), (5, 5)]; max_pool; relu; dense layers after flatten= 0





filters [16, 32, 64]; kernels [(5, 5), (5, 5), (5, 5)]; max_pool; relu; dense layers after flatten= 0


Loss vs epoch
Training
Validation
Loss
Epoch
Accuracy vs epoch
Training
Validation
Accuracy
Epoch

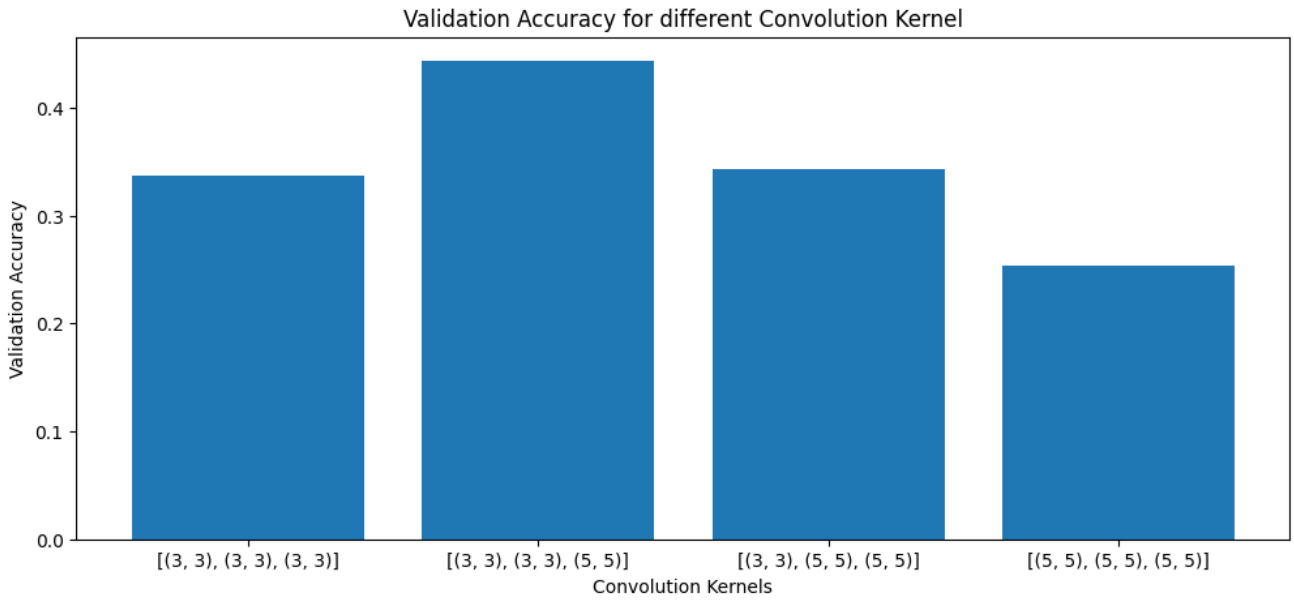

Confusion Matrix for the above model
Actual Value
Predicted Value
0 63 1 0 2
3 1e+02 1 1 1
3 68 0 2 3
0 89 1 1 2
1 81 3 1 3

```
result['Validation f1'] = \
    2*result['Validation Precision']*result['Validation Recall']/(result['Validation Prec
```

```
result
```

	Convolution kernel_size	Convolution filters size	Pooling Layers	Activation	FC layer (after Flatten)	Dropout Rate	Validation Loss	Vali Ac
0	[(3, 3), (3, 3), (3, 3)]	[16, 32, 64]	max	relu	0	0.1	1.513770	0.3
1	[(3, 3), (3, 3), (5, 5)]	[16, 32, 64]	max	relu	0	0.1	1.413185	0.4
	[(3, 3), (5, 5),							

```
plt.figure(figsize=(12, 5))
plt.bar(
    [str(res) for res in result['Convolution kernel_size']],
    result['Validation Accuracy'])
plt.ylabel('Validation Accuracy')
plt.xlabel('Convolution Kernels')
plt.title("Validation Accuracy for different Convolution Kernel")
plt.show()
```




```
best_conv_kernel = result.sort_values(
    by=['Validation Accuracy', 'Validation Loss'],
```

```
    ascending=[False, True]
)['Convolution kernel_size'].iloc[0]

best_conv_kernel
```

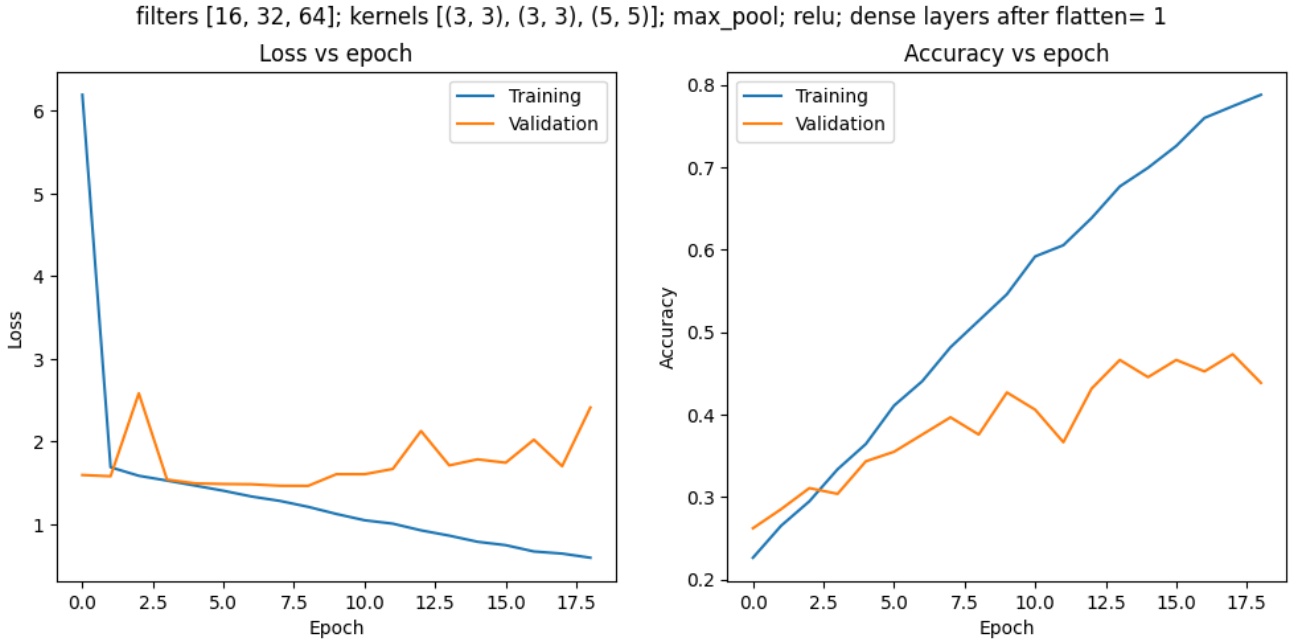
```
[(3, 3), (3, 3), (5, 5)]
```

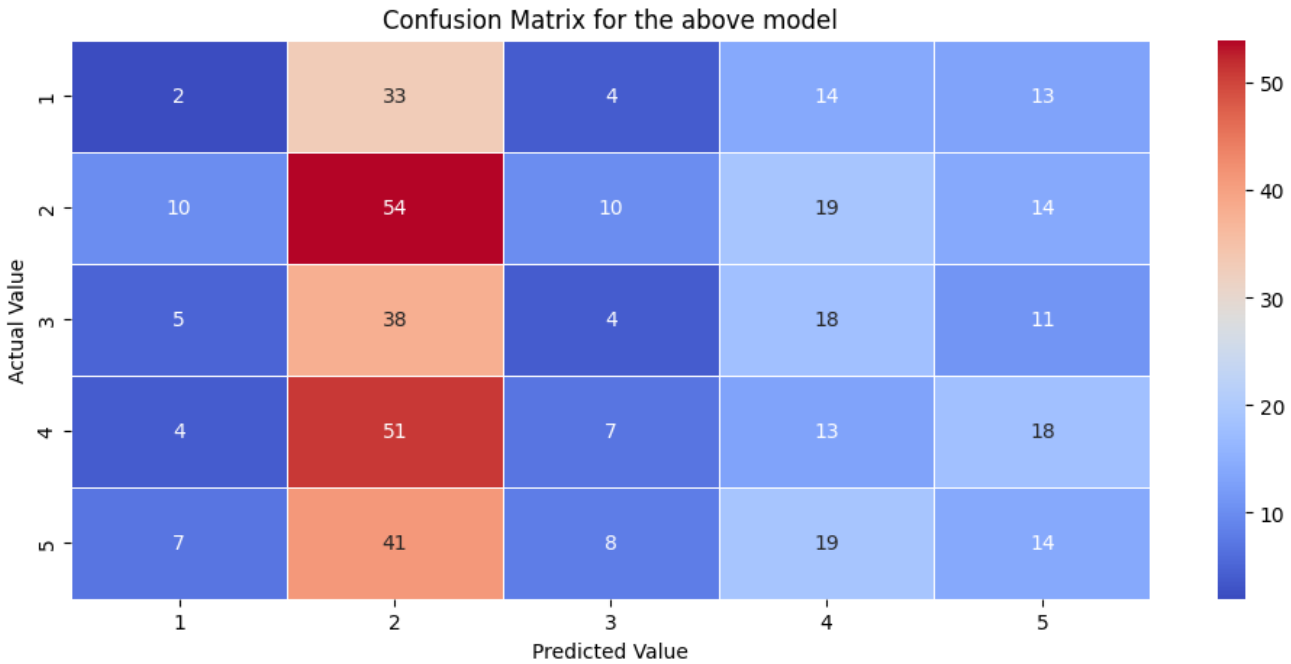
Task 4.2

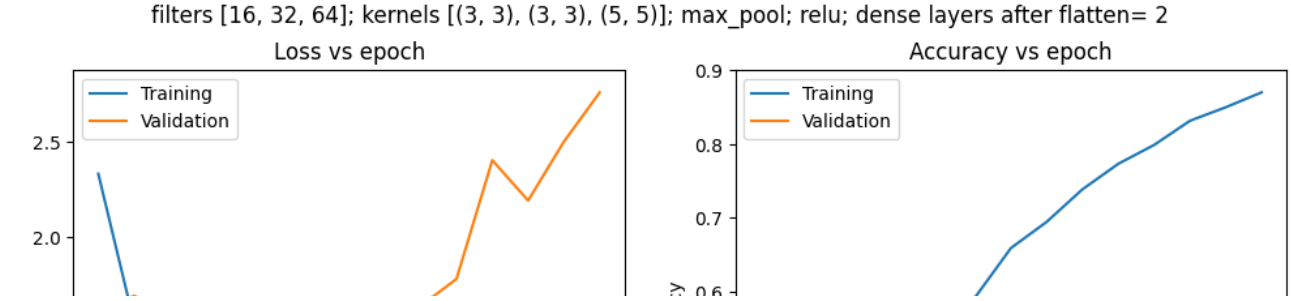
For the best set of parameters obtained above, use two and three FC layers(After Flatten).

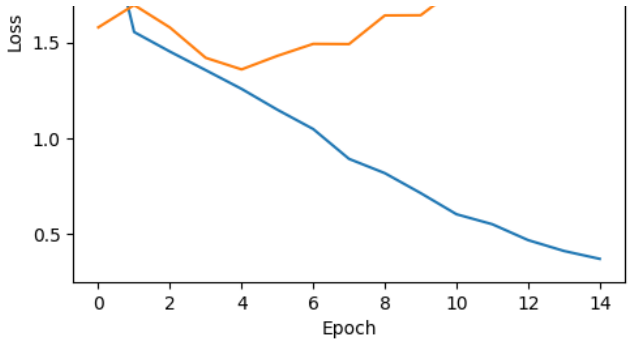
```
result = pd.DataFrame(columns=[
    'Convolution kernel_size',
    'Convolution filters size',
    'Pooling Layers',
    'Activation',
    'FC layer (after Flatten)',
    'Dropout Rate',
    'Validation Loss',
    'Validation Accuracy',
    'Validation Precision',
    'Validation Recall'
])

convolution_filters = [16, 32, 64]
activation = 'relu'
dropout_rate = 0.1
num_fc_layers = [1, 2, 3]
pool = 'max'

for layers in num_fc_layers:
    val_loss, val_acc, val_precision, val_recall = train_model(
        drop_rate=dropout_rate,
        conv_kernels=best_conv_kernel,
        conv_filters=convolution_filters,
        activation=activation,
        pool=pool,
        num_fc_layers=layers,
        train_dataset=train_dataset,
        val_dataset=val_dataset
    )

    result.loc[len(result.index)] = [
        best_conv_kernel,
        convolution_filters,
        pool,
        activation,
        layers,
```

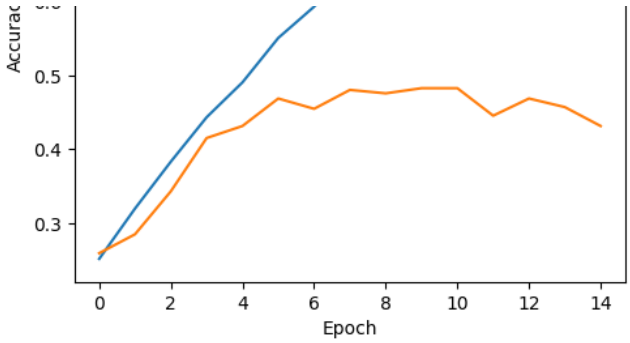
```
    dropout_rate,
    val_loss,
    val_acc,
    val_precision,
    val_recall
]
```

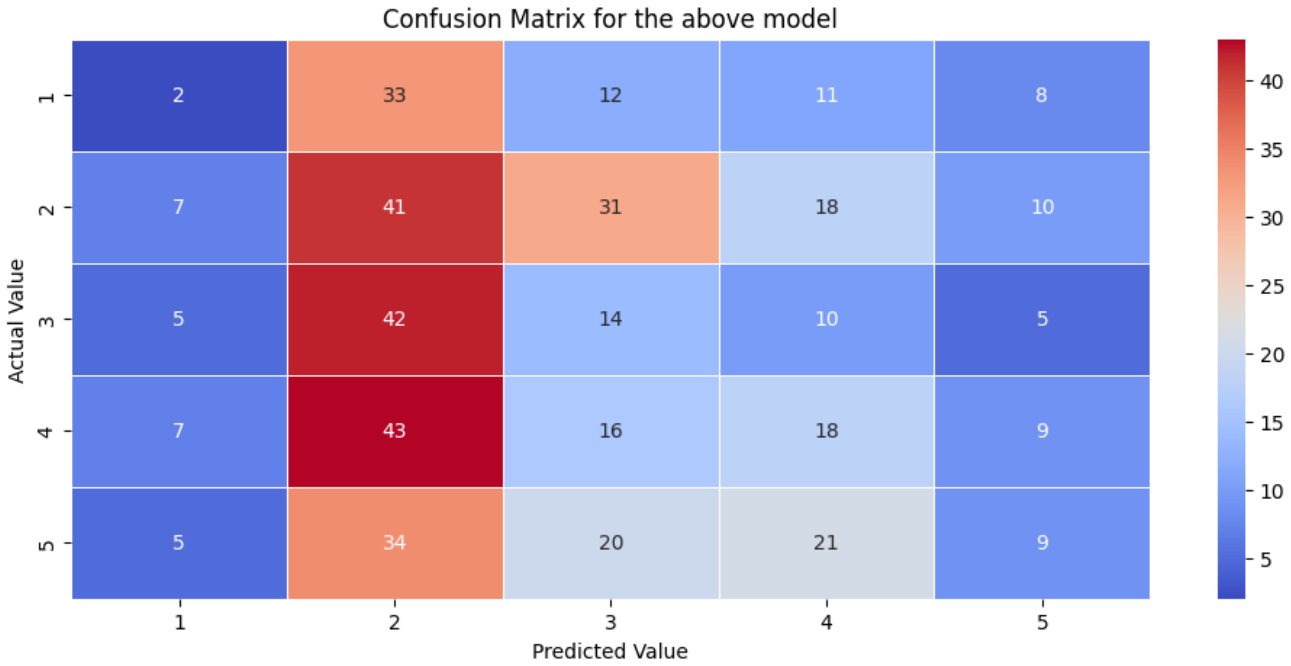




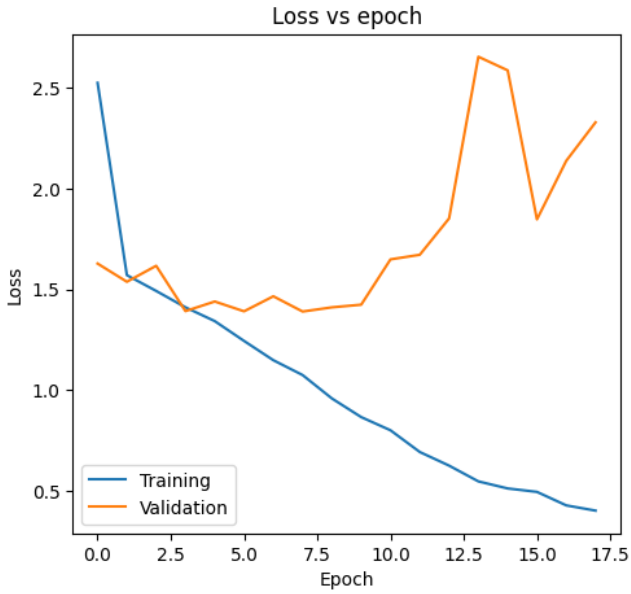


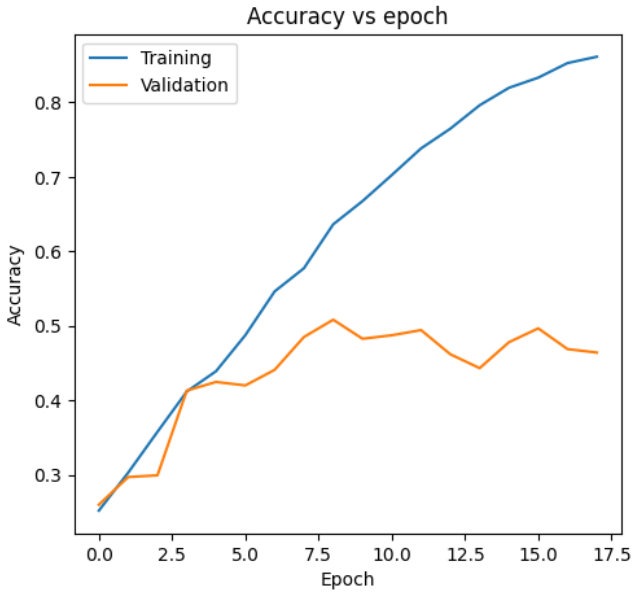


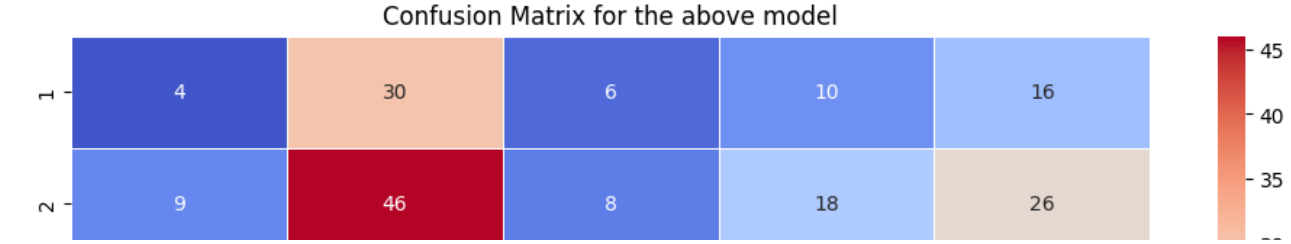


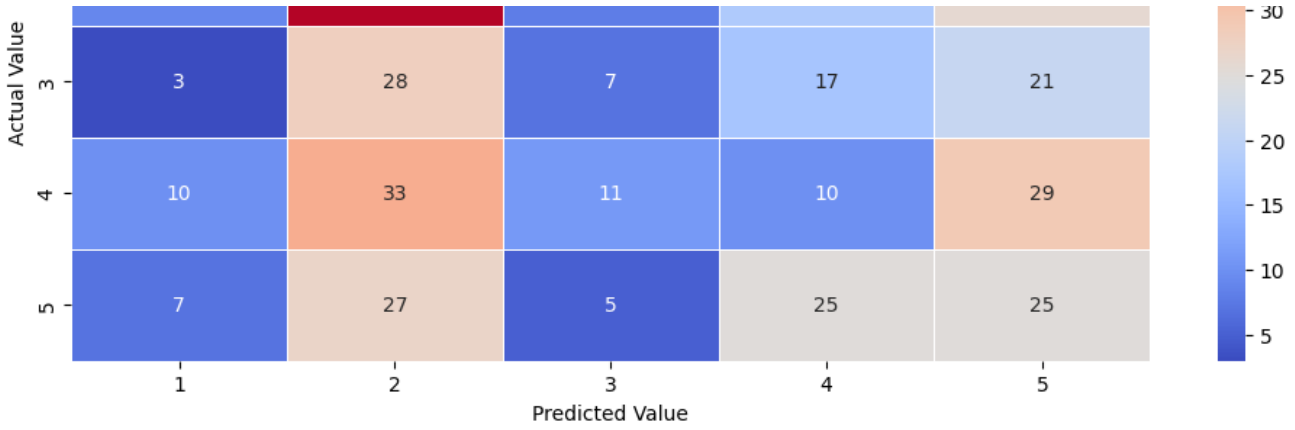


filters [16, 32, 64]; kernels [(3, 3), (3, 3), (5, 5)]; max_pool; relu; dense layers after flatten= 3





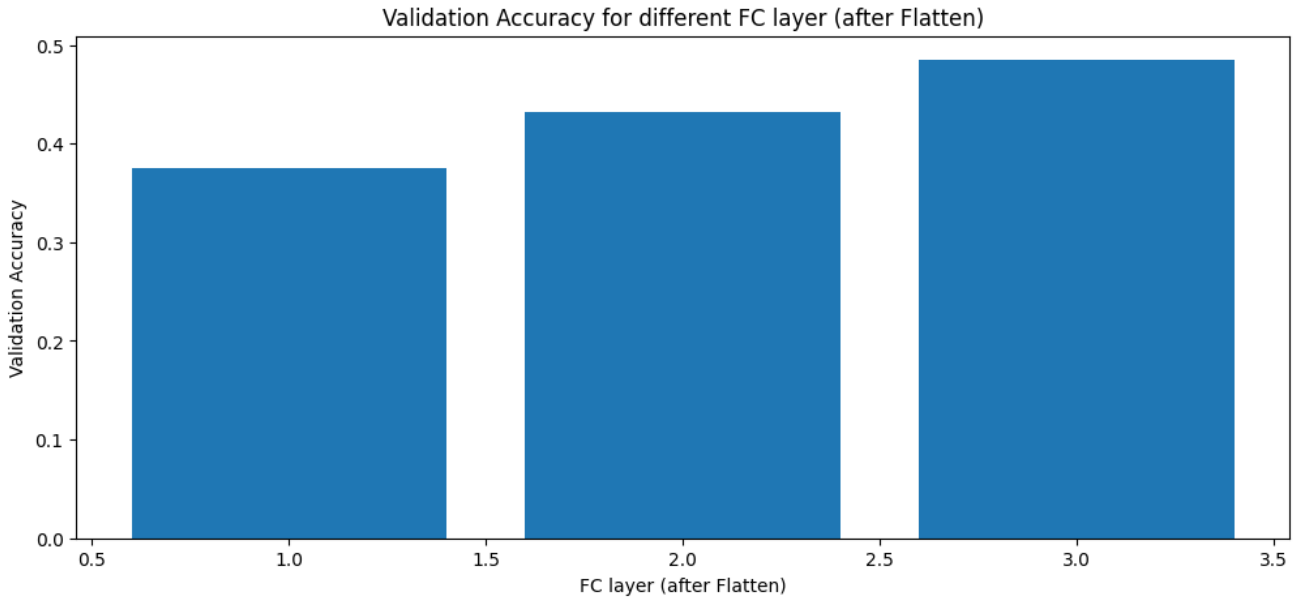



Actual Value
3
4
5
3
28
7
17
21
10
33
11
10
29
7
27
5
25
25
1
2
3
4
5
Predicted Value
30
25
20
15
10
5

```
result['Validation f1'] = \
    2*result['Validation Precision']*result['Validation Recall']/(result['Validation Prec
result
```

	Convolution kernel_size	Convolution filters size	Pooling Layers	Activation	FC layer (after Flatten)	Dropout Rate	Validation Loss	Vali Ac
0	[(3, 3), (3, 3), (5, 5)]	[16, 32, 64]	max	relu	1	0.1	1.465557	0.
1	[(3, 3), (3, 3), (5, 5)]	[16, 32, 64]	max	relu	2	0.1	1.358761	0.

```
plt.figure(figsize=(12, 5))
plt.bar(
    result['FC layer (after Flatten)'],
    result['Validation Accuracy'])
plt.ylabel('Validation Accuracy')
plt.xlabel('FC layer (after Flatten)')
plt.title("Validation Accuracy for different FC layer (after Flatten)")
plt.show()
```



```
best_num_fc_layers = result.sort_values(
    by=['Validation Accuracy', 'Validation Loss'],
    ascending=[False, True]
    )['FC layer (after Flatten)'].iloc[0]

best_num_fc_layers
```

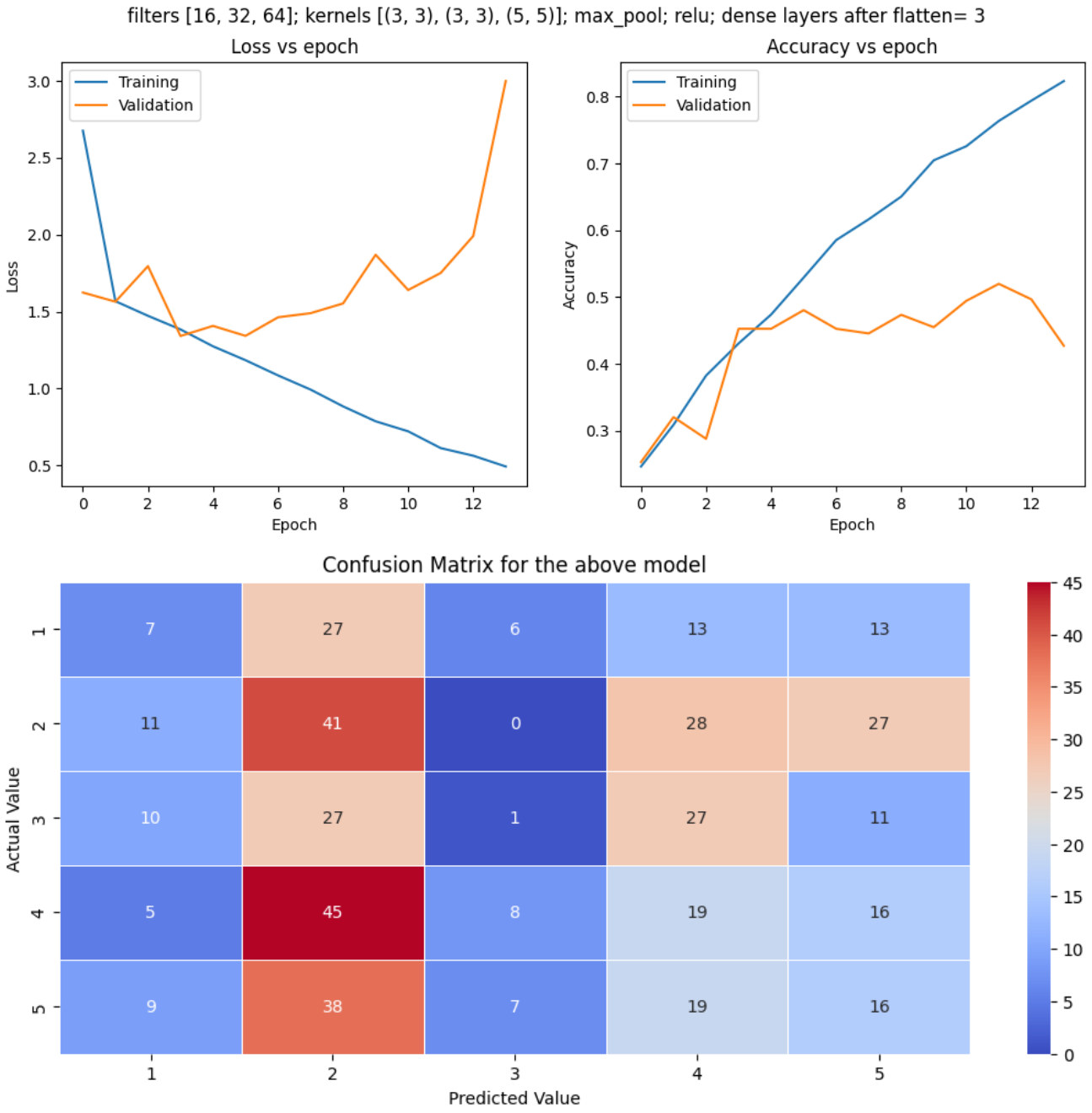
```
3
```

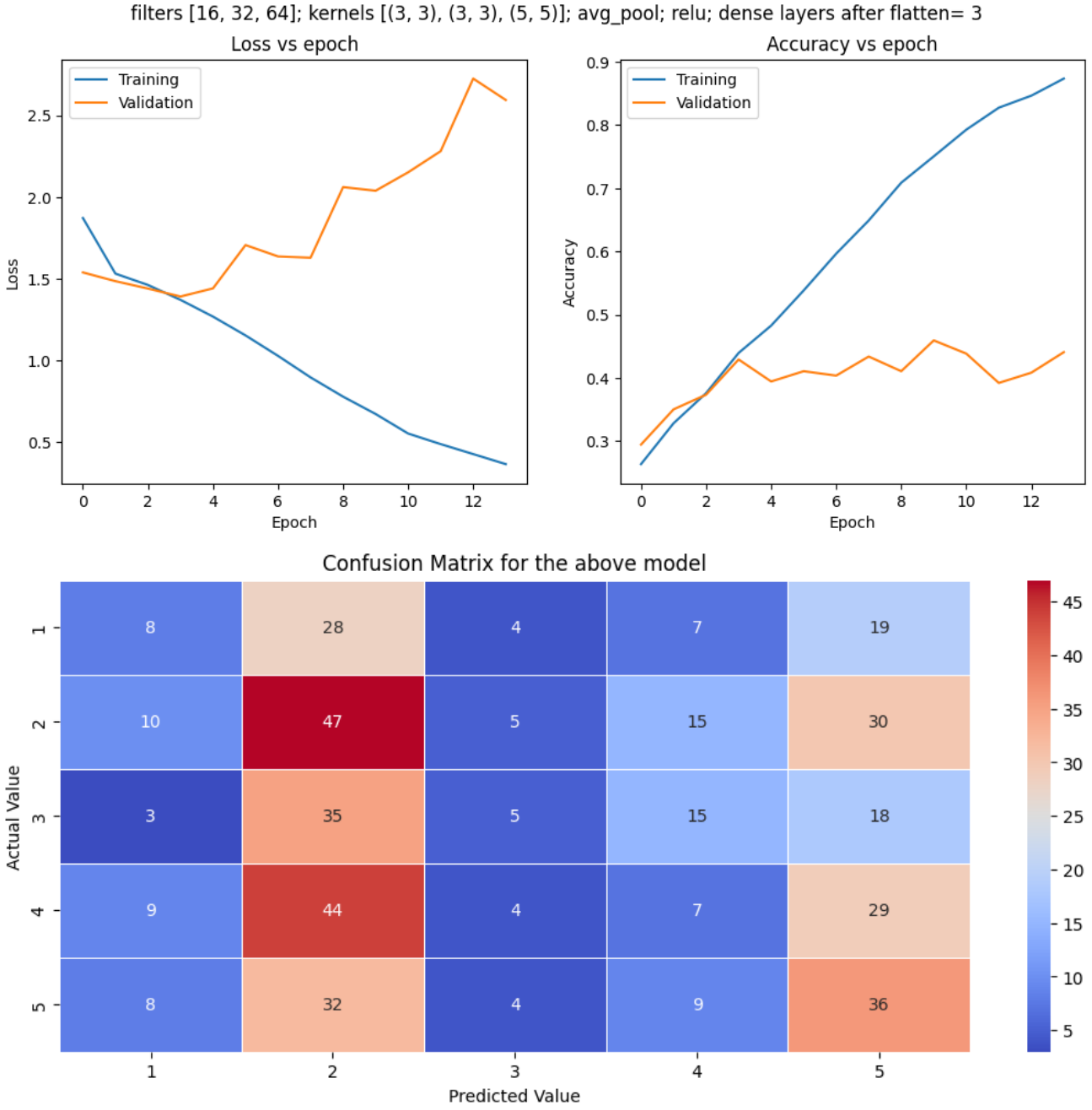
Task 4.3

For the best set of parameters obtained above, use average pooling instead of Max pooling.

```
result = pd.DataFrame(columns=[
    'Convolution kernel_size',
    'Convolution filters size',
    'Pooling Layers',
    'Activation',
    'FC layer (after Flatten)',
    'Dropout Rate',
    'Validation Loss',
    'Validation Accuracy',
    'Validation Precision',
    'Validation Recall'
])

convolution_filters = [16, 32, 64]
activation = 'relu'
dropout_rate = 0.1
pools = ['max', 'avg']

for pool in pools:
    val_loss, val_acc, val_precision, val_recall = train_model(
        drop_rate=dropout_rate,
        conv_kernels=best_conv_kernel,
        conv_filters=convolution_filters,
        activation=activation,
        pool=pool,
        num_fc_layers=best_num_fc_layers,
        train_dataset=train_dataset,
        val_dataset=val_dataset
```

```
    val_dataset=val_dataset
)

result.loc[len(result.index)] = [
    best_conv_kernel,
    convolution_filters,
    pool,
    activation,
    best_num_fc_layers,
    dropout_rate,
    val_loss,
    val_acc,
    val_precision,
    val_recall
]
```

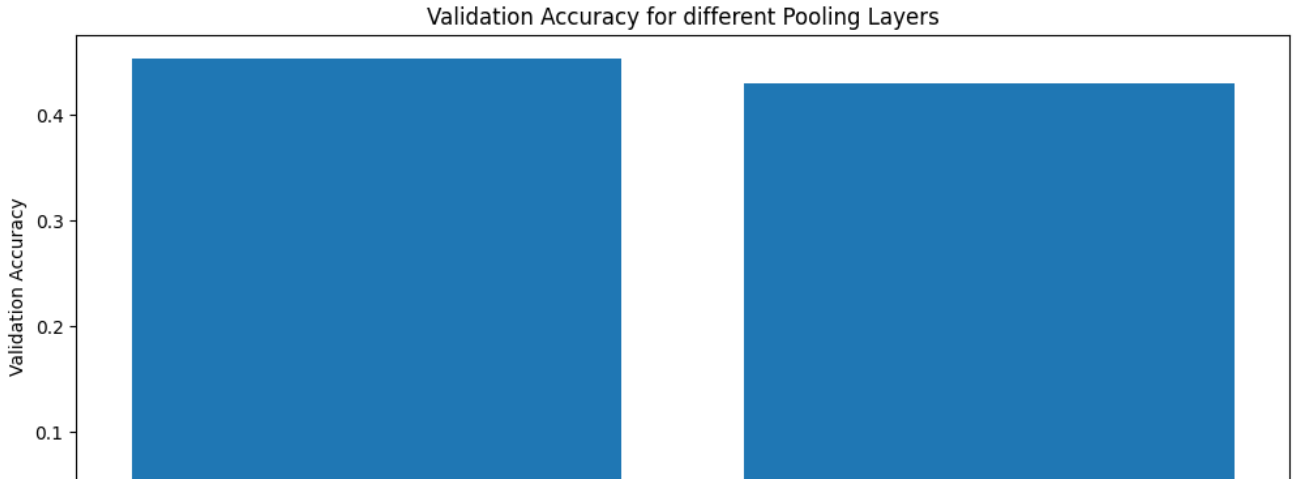


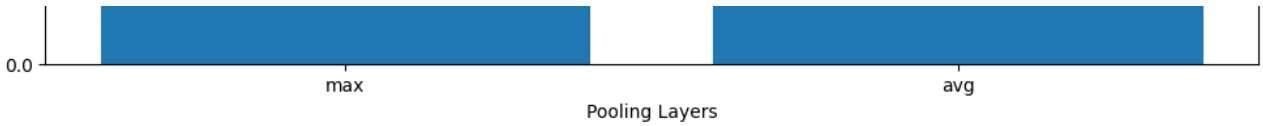

filters [16, 32, 64]; kernels [(3, 3), (3, 3), (5, 5)]; avg_pool; relu; dense layers after flatten= 3
Loss vs epoch
Training
Validation
Loss
Epoch
Accuracy vs epoch
Training
Validation
Accuracy
Epoch
Confusion Matrix for the above model
Actual Value
Predicted Value
8 28 4 7 19
10 47 5 15 30
3 35 5 15 18
9 44 4 7 29
8 32 4 9 36

```
result['Validation f1'] = \
    2*result['Validation Precision']*result['Validation Recall']/(result['Validation Prec
result
```

	Convolution kernel_size	Convolution filters size	Pooling Layers	Activation	FC layer (after Flatten)	Dropout Rate	Validation Loss	Vali Ac
0	[(3, 3), (3, 3), (5, 5)]	[16, 32, 64]	max	relu	3	0.1	1.341094	0.4

```
plt.figure(figsize=(12, 5))
plt.bar(
    result['Pooling Layers'],
    result['Validation Accuracy'])
plt.ylabel('Validation Accuracy')
plt.xlabel('Pooling Layers')
plt.title("Validation Accuracy for different Pooling Layers")
plt.show()
```






```
best_pool = result.sort_values(
    by=['Validation Accuracy', 'Validation Loss'],
    ascending=[False, True]
    )['Pooling Layers'].iloc[0]

best_pool
```

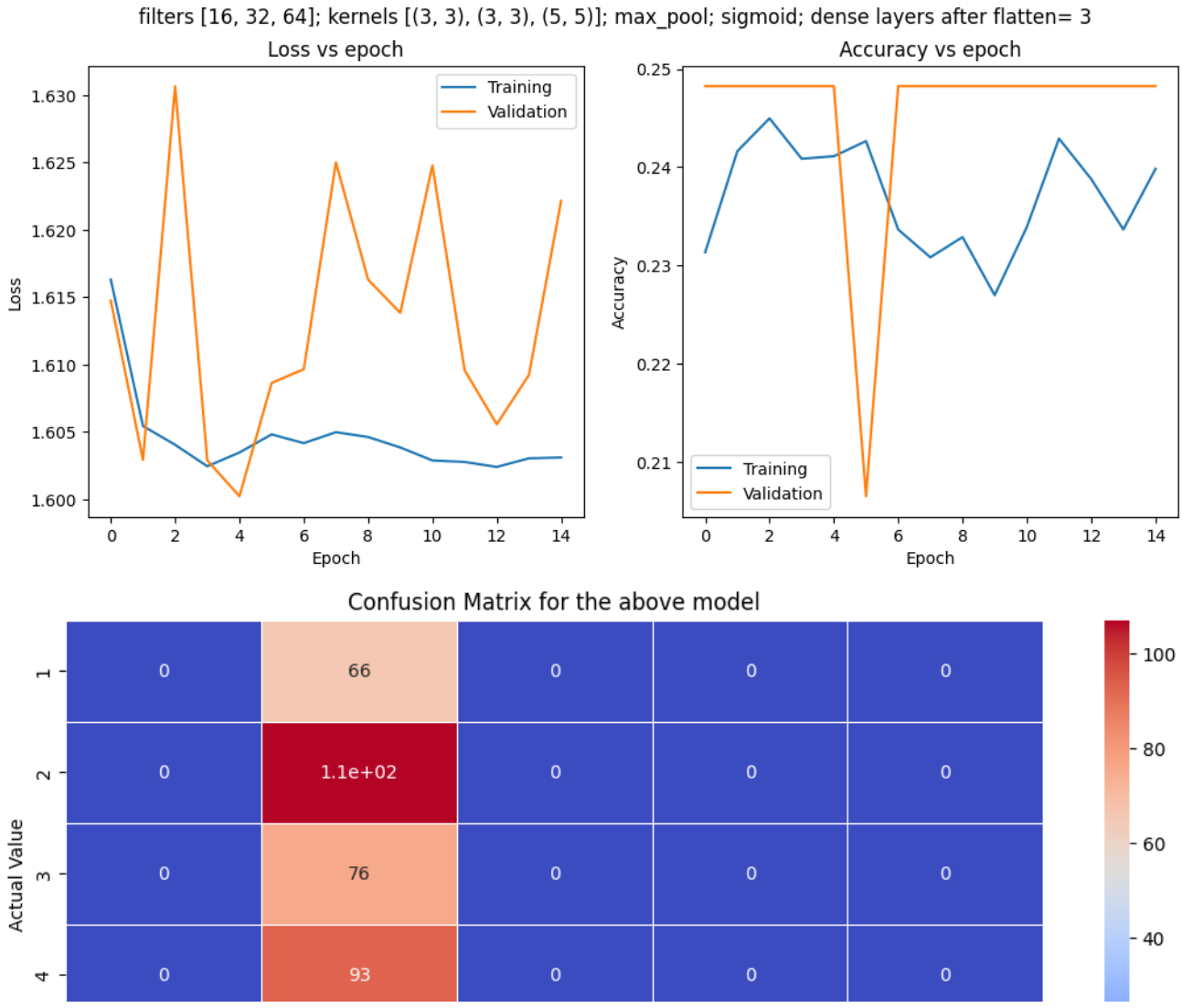
```
 'max'
```

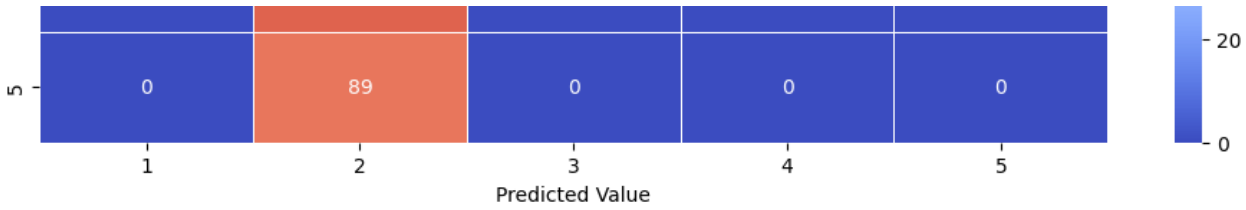
Task 4.4

For the best set of parameters obtained above, use the activation function: Sigmoid, ELU, Leaky Relu (alpha= 0.01)

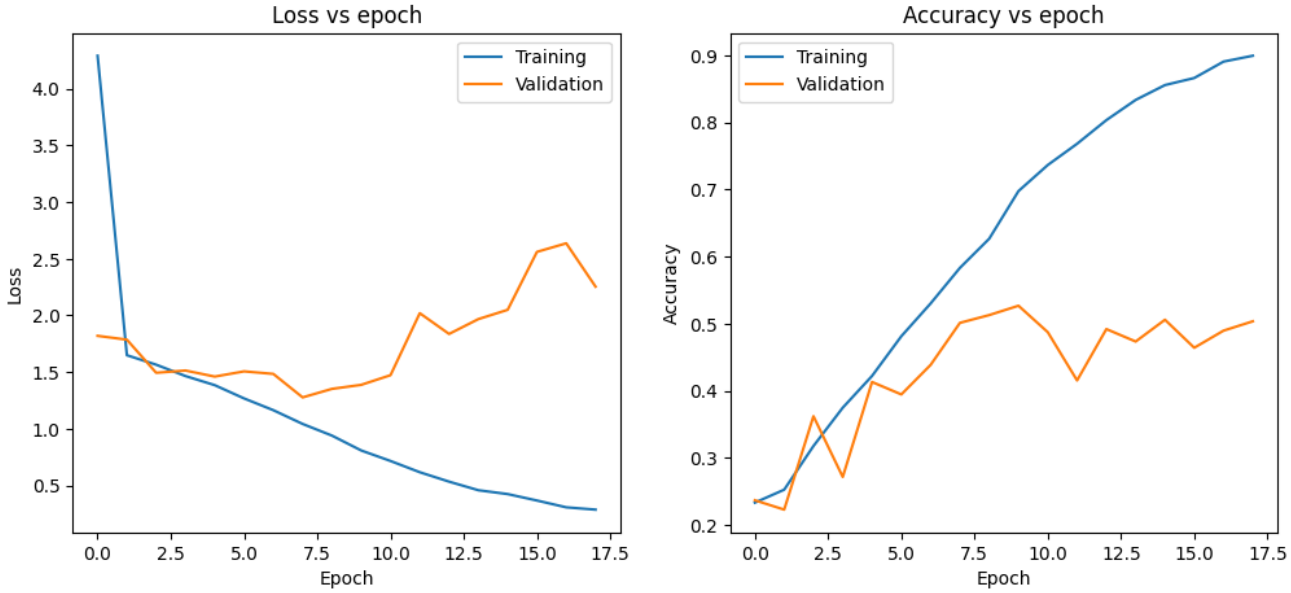
```
result = pd.DataFrame(columns=[
    'Convolution kernel_size',
    'Convolution filters size',
    'Pooling Layers',
    'Activation',
    'FC layer (after Flatten)',
    'Dropout Rate',
    'Validation Loss',
    'Validation Accuracy',
    'Validation Precision',
    'Validation Recall'
])

convolution_filters = [16, 32, 64]
activations = ['sigmoid', 'elu', 'relu', 'lrelu']
dropout_rate = 0.1

for activation in activations:
    val_loss, val_acc, val_precision, val_recall = train_model(
        drop_rate=dropout_rate,
        conv_kernels=best_conv_kernel,
```

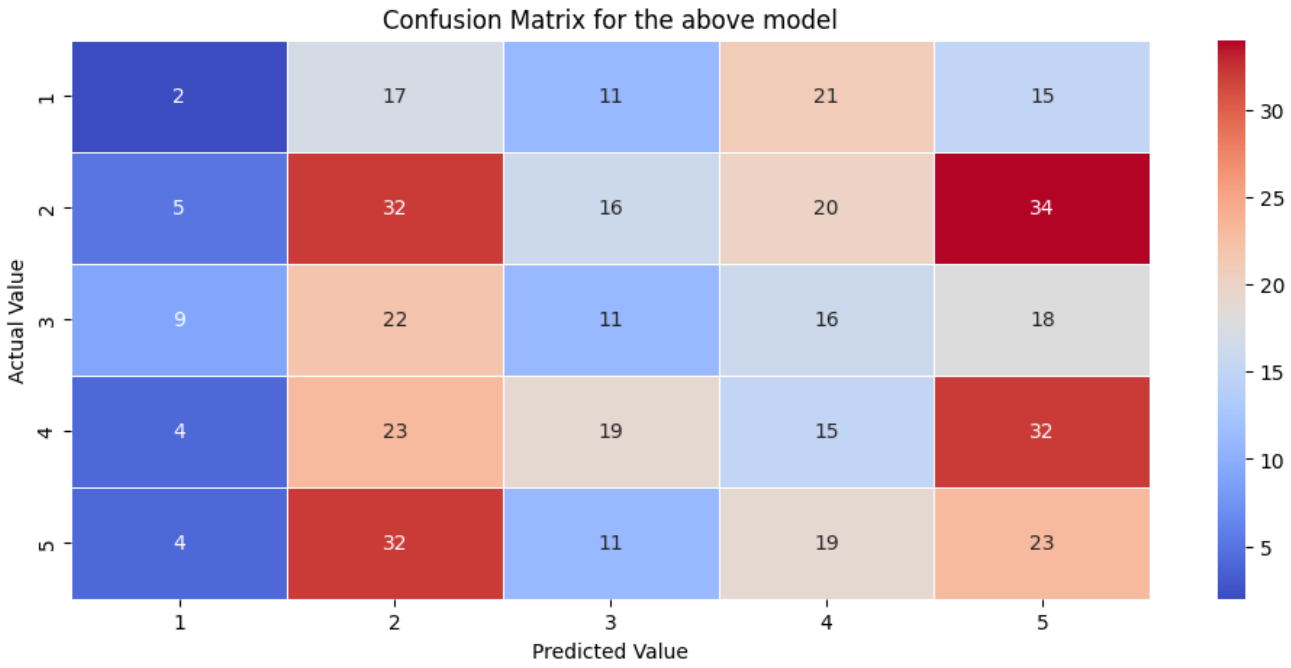
```
    conv_filters=convolution_filters,
    activation=activation,
    pool=best_pool,
    num_fc_layers=best_num_fc_layers,
    train_dataset=train_dataset,
    val_dataset=val_dataset
)

result.loc[len(result.index)] = [
    best_conv_kernel,
    convolution_filters,
    best_pool,
    activation,
    best_num_fc_layers,
    dropout_rate,
    val_loss,
    val_acc,
    val_precision,
    val_recall
]
```



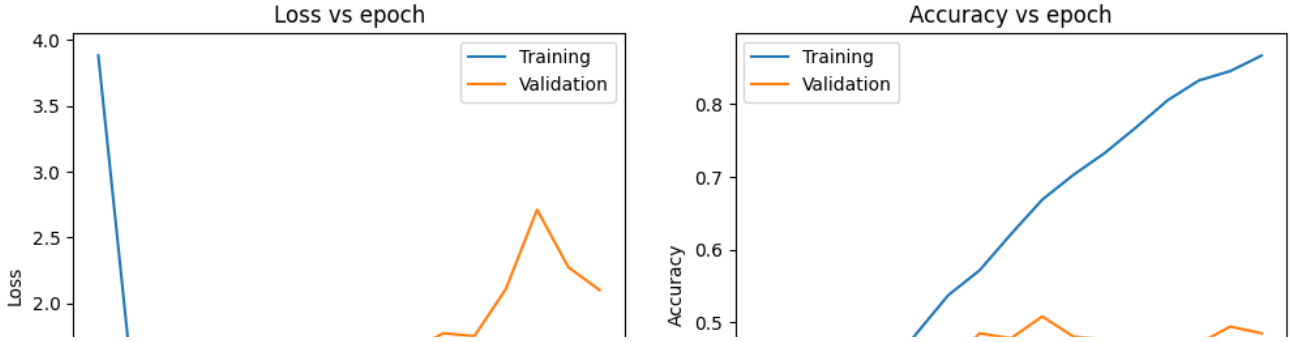


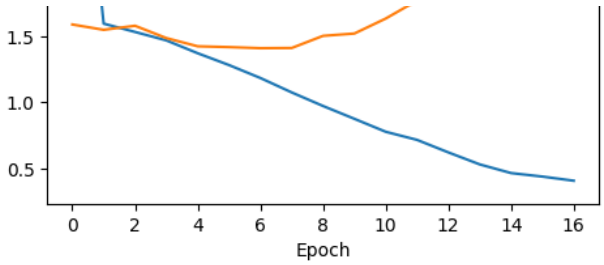
filters [16, 32, 64]; kernels [(3, 3), (3, 3), (5, 5)]; max_pool; elu; dense layers after flatten= 3

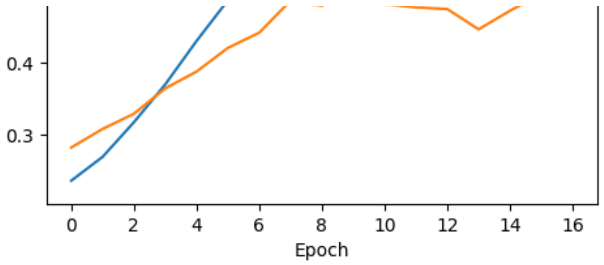


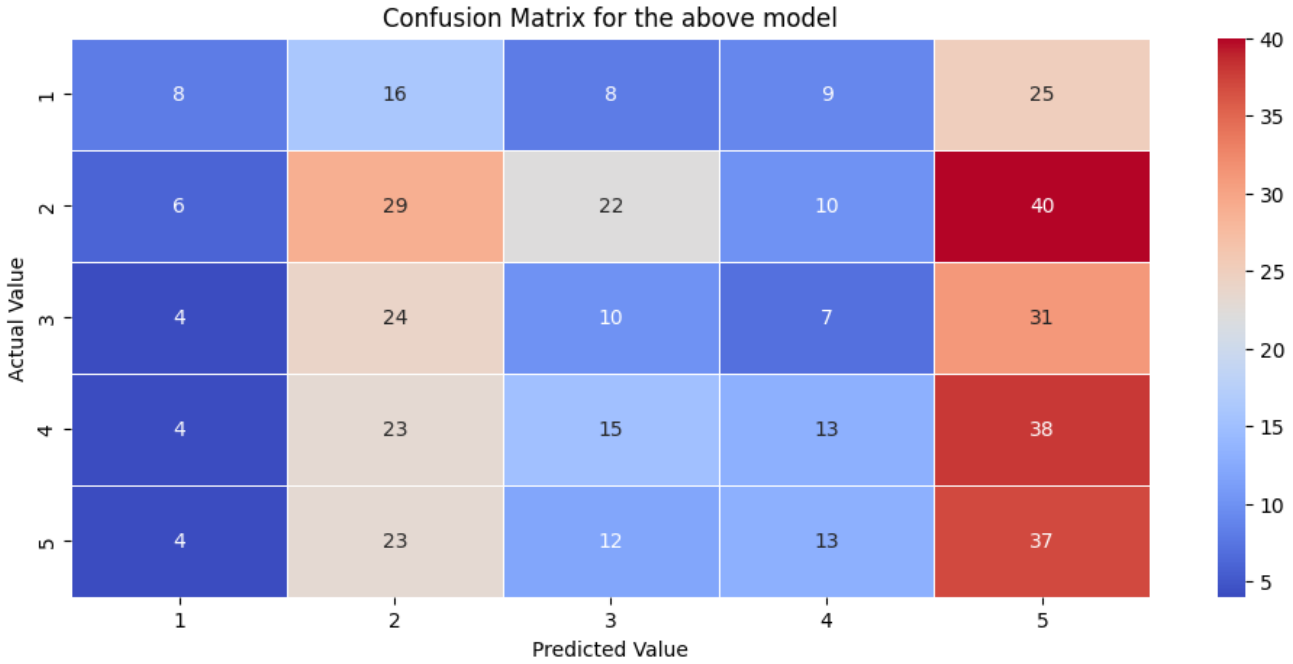


filters [16, 32, 64]; kernels [(3, 3), (3, 3), (5, 5)]; max_pool; relu; dense layers after flatten= 3

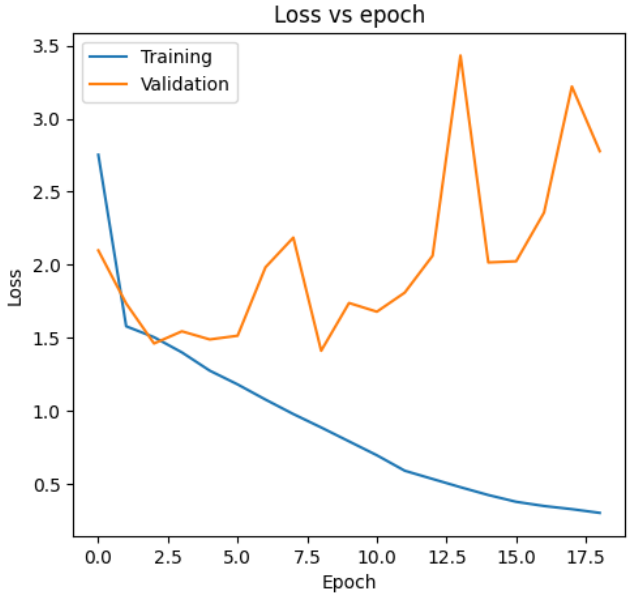


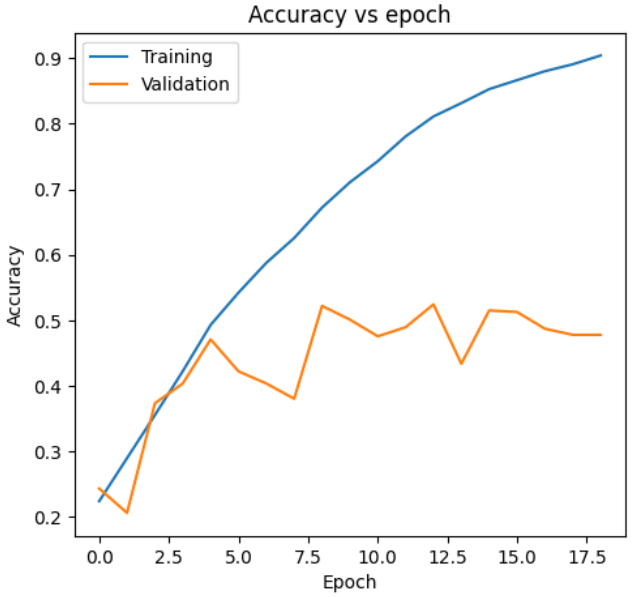


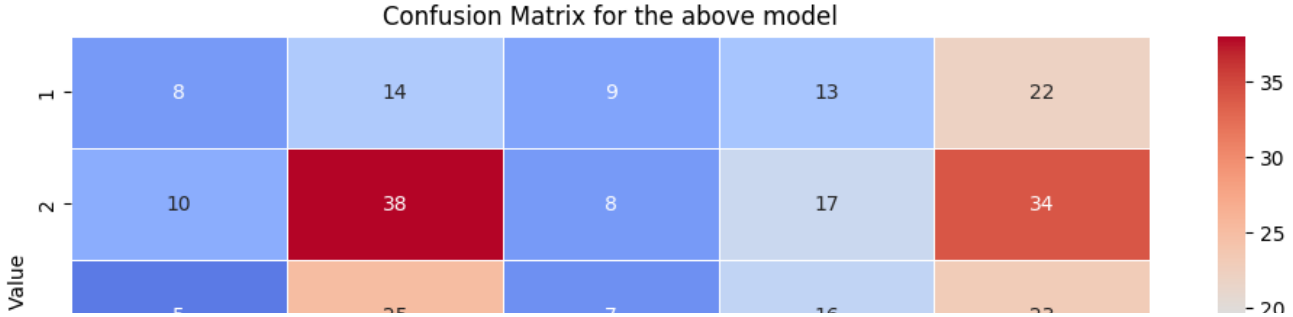


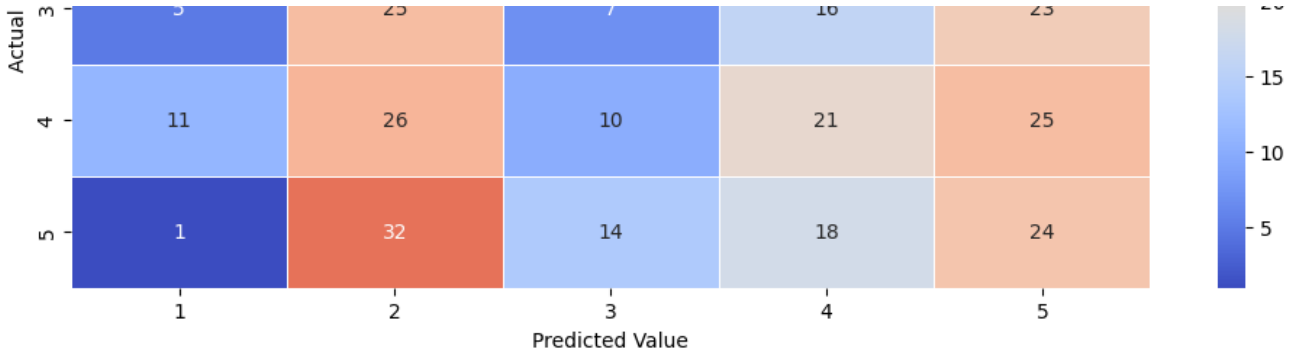


filters [16, 32, 64]; kernels [(3, 3), (3, 3), (5, 5)]; max_pool; lrelu; dense layers after flatten= 3





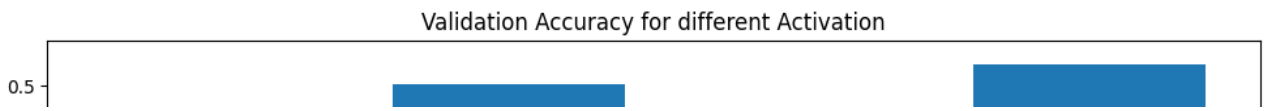


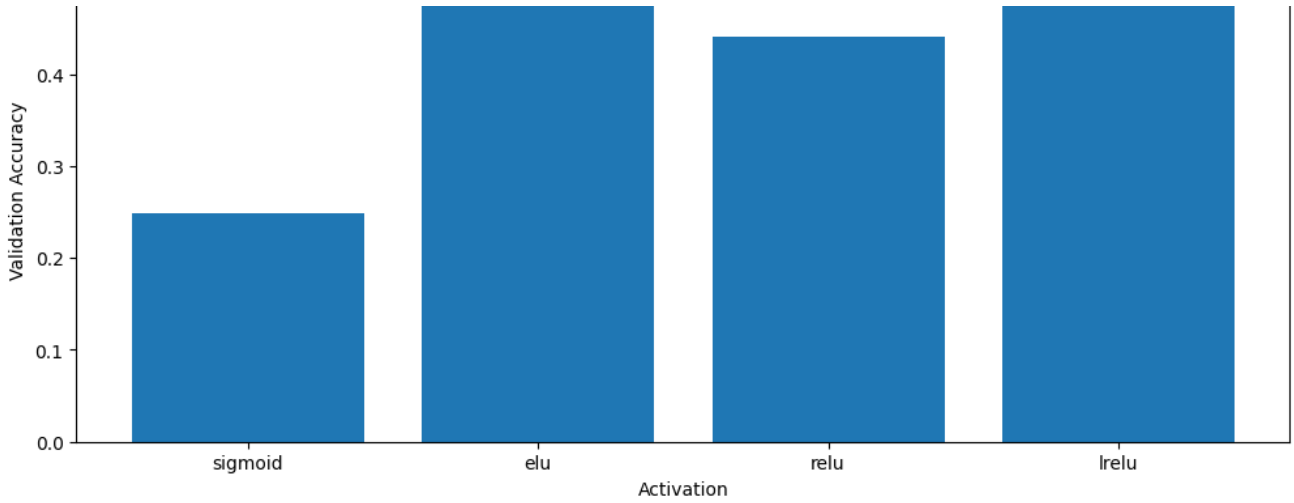

Actual
3
4
5
11
26
10
21
25
1
32
14
18
24
1
2
3
4
5
Predicted Value
15
10
5

```
result['Validation f1'] = \
    2*result['Validation Precision']*result['Validation Recall']/(result['Validation Prec
result
```

	Convolution kernel_size	Convolution filters size	Pooling Layers	Activation	FC layer (after Flatten)	Dropout Rate	Validation Loss	Vali Ac
0	[(3, 3), (3, 3), (5, 5)]	[16, 32, 64]	max	sigmoid	3	0.1	1.600221	0.2
1	[(3, 3), (3, 3), (5, 5)]	[16, 32, 64]	max	elu	3	0.1	1.277071	0.
	[(3, 3), (3, 3),							

```
plt.figure(figsize=(12, 5))
plt.bar(
    result['Activation'],
    result['Validation Accuracy'])
plt.ylabel('Validation Accuracy')
plt.xlabel('Activation')
plt.title("Validation Accuracy for different Activation")
plt.show()
```






```
best_activation = result.sort_values(
    by=['Validation Accuracy', 'Validation Loss'],
    ascending=[False, True]
    )['Activation'].iloc[0]

best_activation
```

```
'lrelu'
```

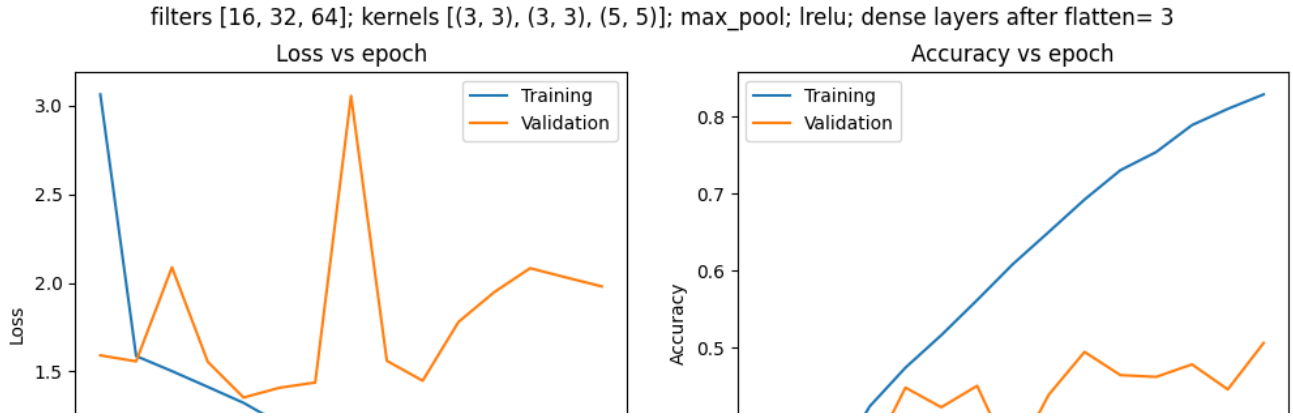
Task 4.5

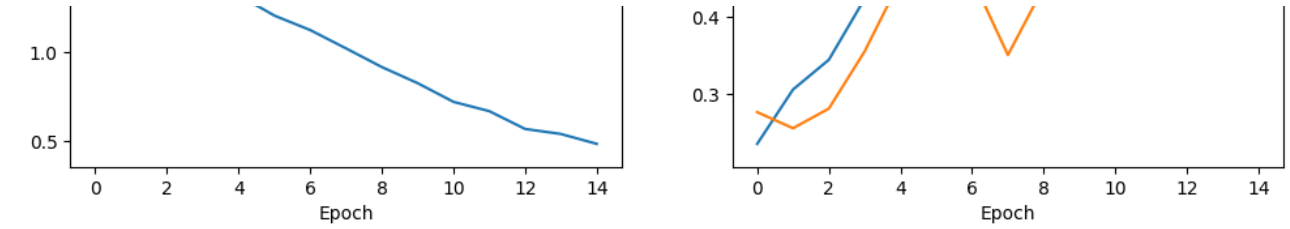
For the best set of parameters fromtheaboverunsvarythe regularization parameter:

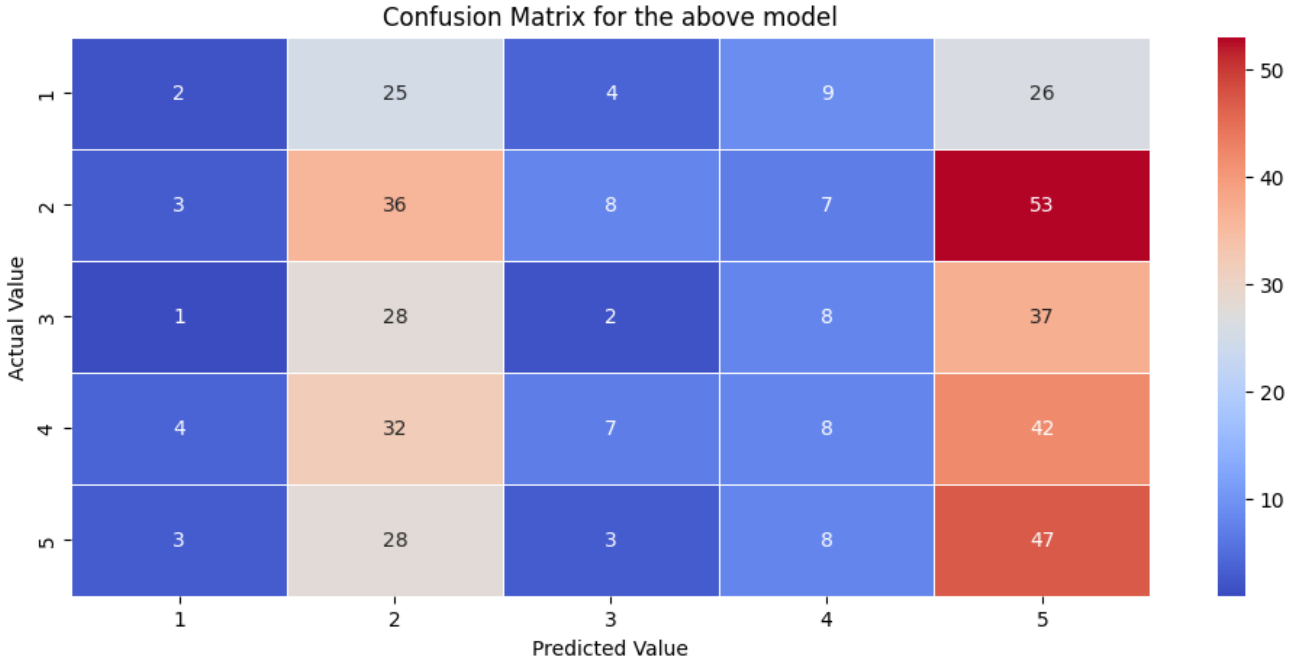
Regularization
Dropout of 0.1 after each layer
Dropout of 0.25 after each layer
Batch Normalization after each layer (except the first)
Dropout of 0.1 after each layer along with Batch Normalization after each layer (except the first)

```
result = pd.DataFrame(columns=[
    'Convolution kernel_size',
    'Convolution filters size',
    'Pooling Layers',
    'Activation',
    'FC layer (after Flatten)',
```

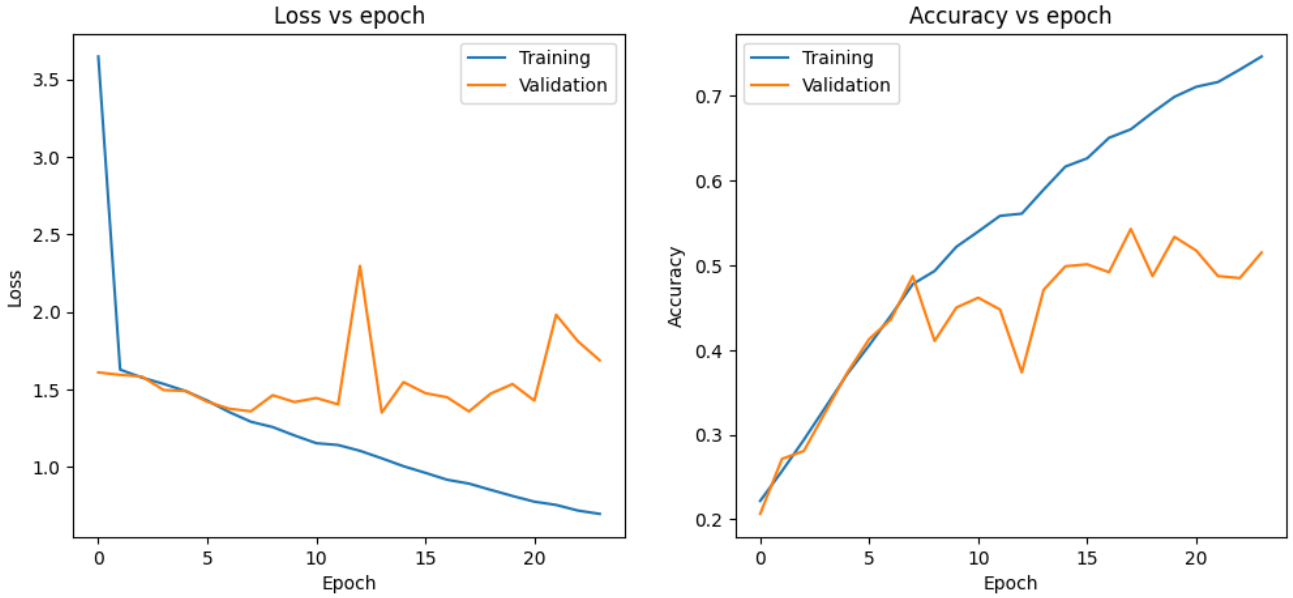
```
    'Dropout Rate',
    'Batch Normalization Present',
    'Validation Loss',
    'Validation Accuracy',
    'Validation Precision',
    'Validation Recall'
])

convolution_filters = [16, 32, 64]
dropout_rates = [0.1, 0.25, 0, 0.1]
batch_norm_cases = [False, False, True, True]

for dropout_rate, do_batch in zip(dropout_rates, batch_norm_cases):
    val_loss, val_acc, val_precision, val_recall = train_model(
        drop_rate=dropout_rate,
        conv_kernels=best_conv_kernel,
        conv_filters=convolution_filters,
        activation=best_activation,
        pool=best_pool,
        add_batch_norm=do_batch,
        num_fc_layers=best_num_fc_layers,
        train_dataset=train_dataset,
        val_dataset=val_dataset
    )

    result.loc[len(result.index)] = [
        best_conv_kernel,
        convolution_filters,
        best_pool,
        best_activation,
        best_num_fc_layers,
        dropout_rate,
        do_batch,
        val_loss,
        val_acc,
        val_precision,
        val_recall
    ]
```

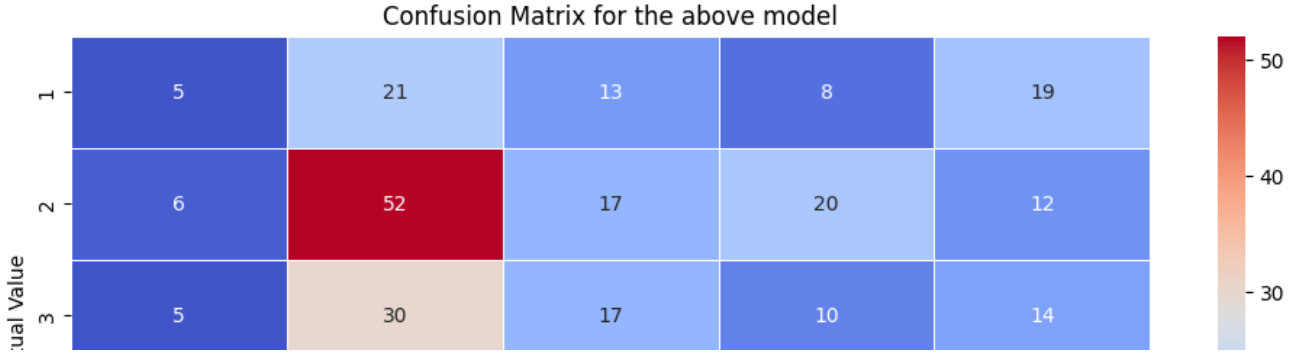


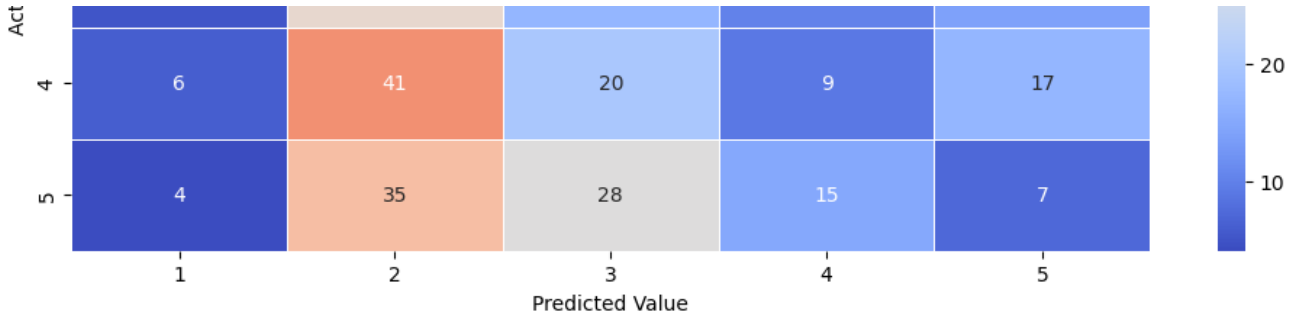




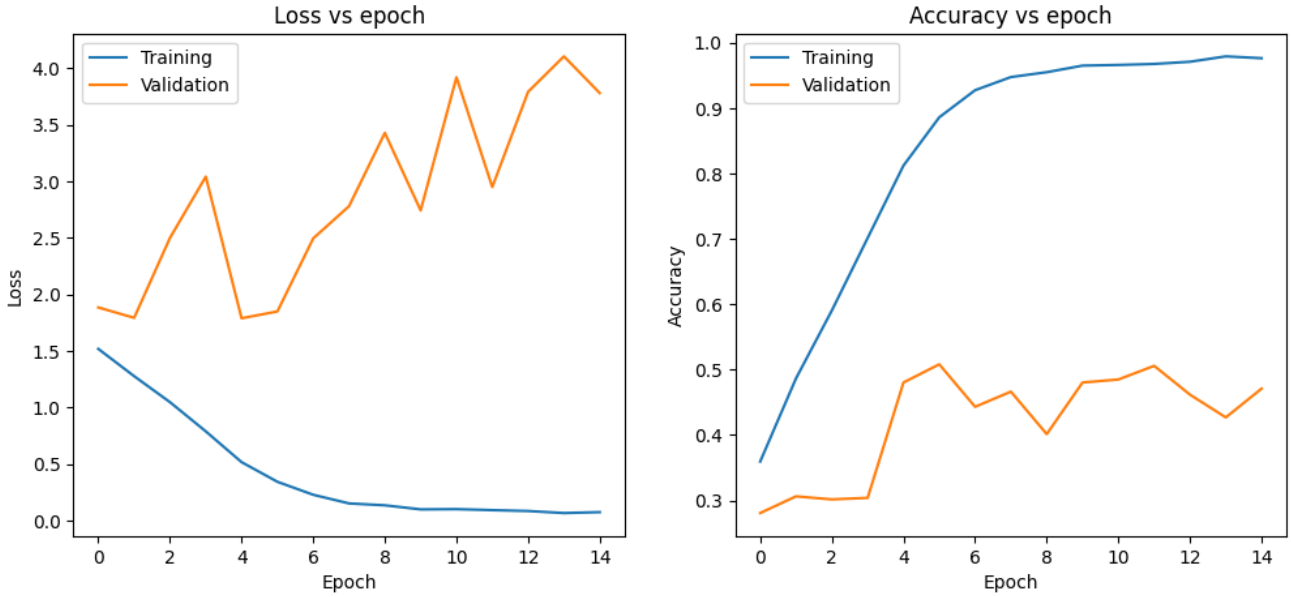
filters [16, 32, 64]; kernels [(3, 3), (3, 3), (5, 5)]; max_pool; lrelu; dense layers after flatten= 3

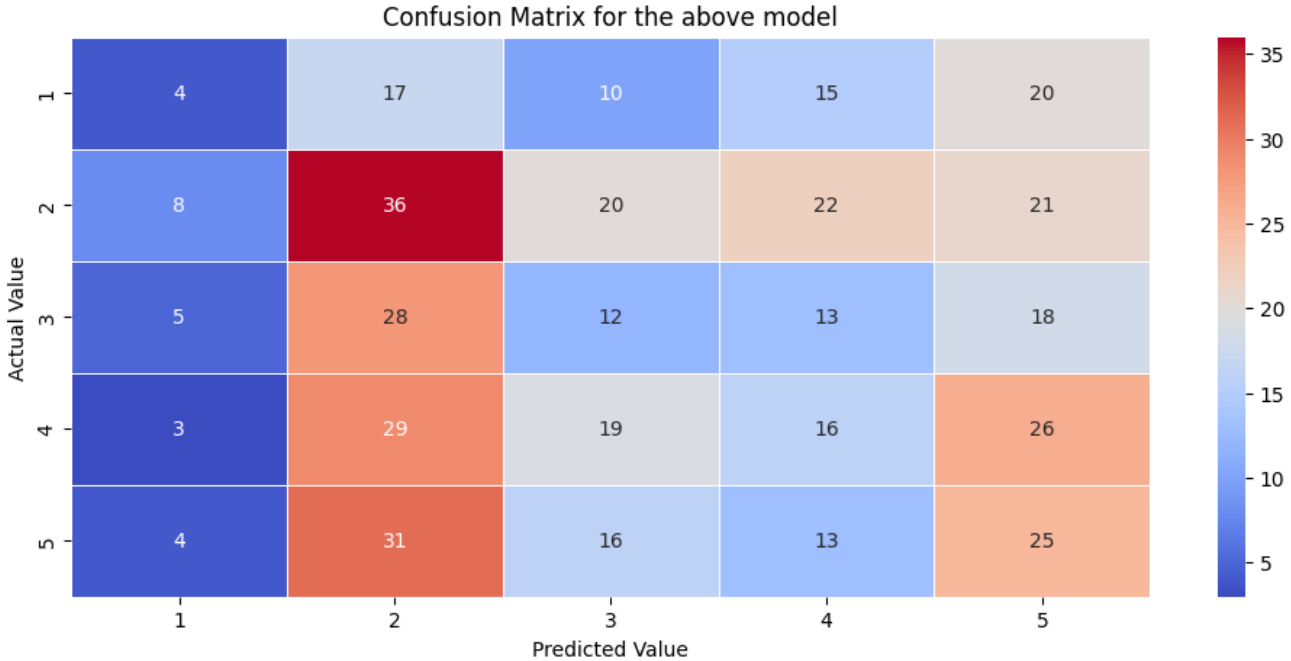




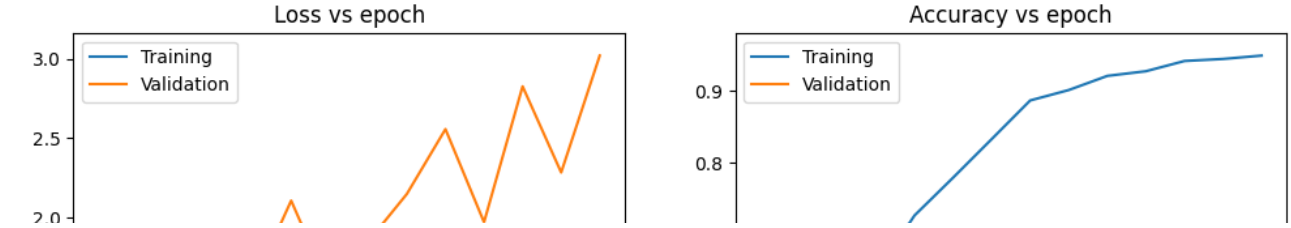


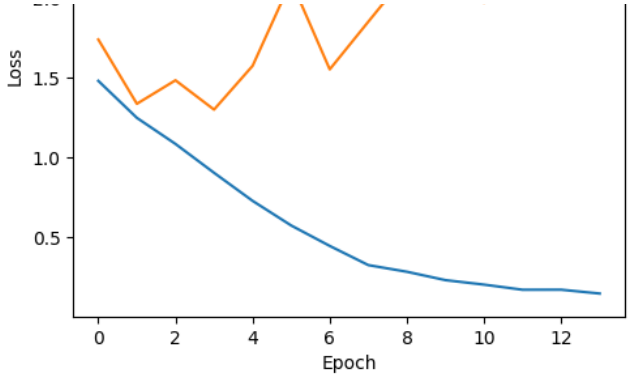
filters [16, 32, 64]; kernels [(3, 3), (3, 3), (5, 5)]; max_pool; lrelu; dense layers after flatten= 3

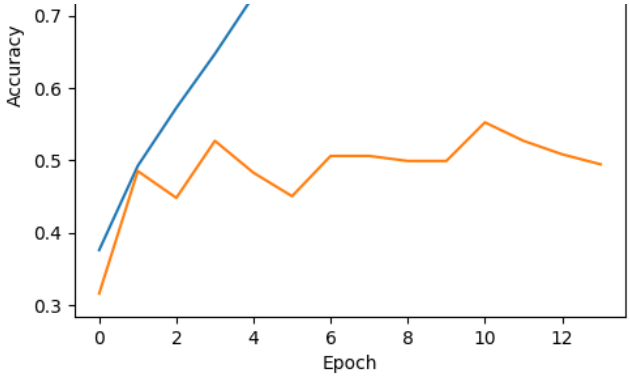


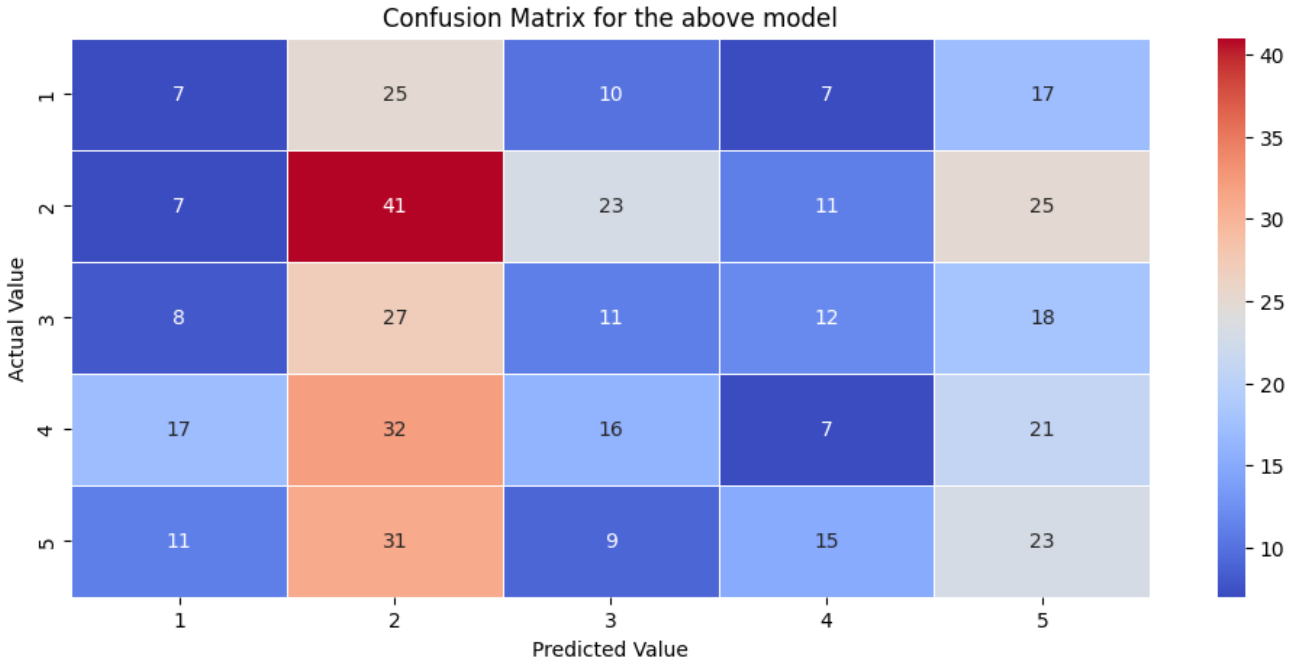


filters [16, 32, 64]; kernels [(3, 3), (3, 3), (5, 5)]; max_pool; lrelu; dense layers after flatten= 3




Loss
1.5
1.0
0.5
0
2
4
6
8
10
12
Epoch


Accuracy
0.7
0.6
0.5
0.4
0.3
0
2
4
6
8
10
12
Epoch

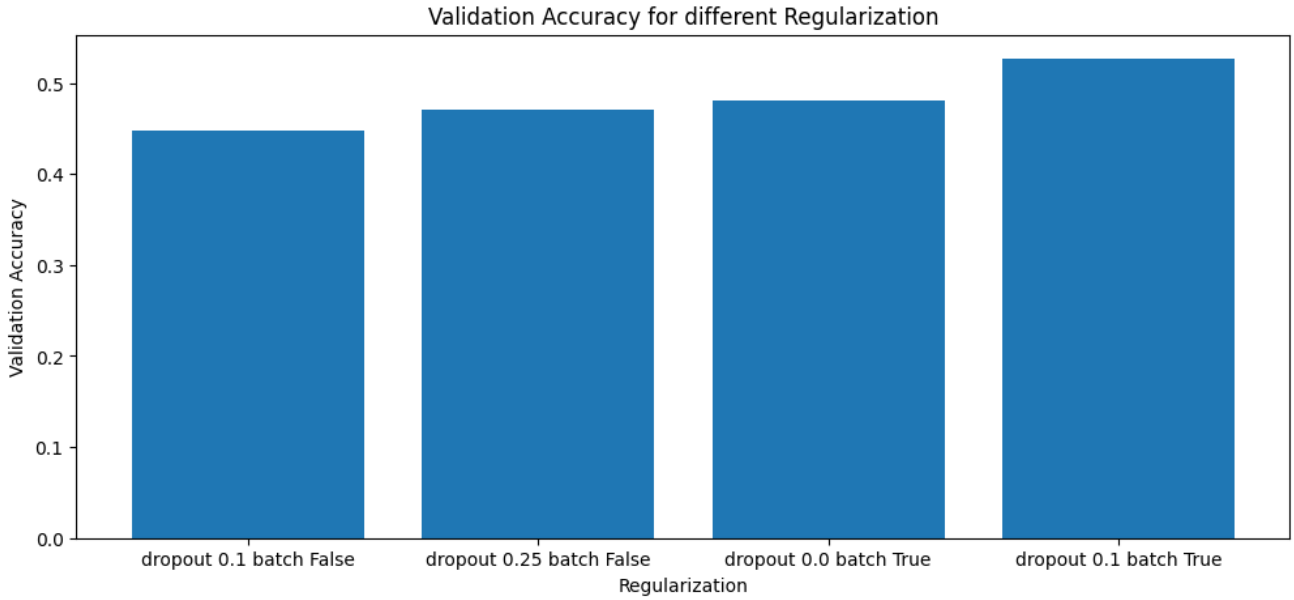

Confusion Matrix for the above model
Actual Value
Predicted Value
1
2
3
4
5
7 25 10 7 17
7 41 23 11 25
8 27 11 12 18
17 32 16 7 21
11 31 9 15 23
40
35
30
25
20
15
10

```
result['Validation f1'] = \
    2*result['Validation Precision']*result['Validation Recall']/(result['Validation Prec
result
```

	Convolution kernel_size	Convolution filters size	Pooling Layers	Activation	FC layer (after Flatten)	Dropout Rate	Batch Normalization Present	V
	[(3, 3), (3, 3)]							

0	[(3, 3), (3, 3), (5, 5)]	[16, 32, 64]	max	lrelu	3	0.10	False
1	[(3, 3), (3, 3), (5, 5)]	[16, 32, 64]	max	lrelu	3	0.25	False
2	[(3, 3), (3, 3), (5, 5)]	[16, 32, 64]	max	lrelu	3	0.00	True
3	[(3, 3), (3, 3), (5, 5)]	[16, 32, 64]	max	lrelu	3	0.10	True

```
plt.figure(figsize=(12, 5))
plt.bar(
    [f'dropout {drop} batch {batch}' for drop,batch in zip(result['Dropout Rate'], result
    result['Validation Accuracy'])
plt.ylabel('Validation Accuracy')
plt.xlabel('Regularization')
plt.title("Validation Accuracy for different Regularization")
plt.show()
```




```
best_dropout = result.sort_values(
    by=['Validation Accuracy', 'Validation Loss'],
    ascending=[False, True]
    )['Dropout Rate'].iloc[0]
```

```
print(f"best dropout rate: {best_dropout}")

best_do_batch = result.sort_values(
    by=['Validation Accuracy', 'Validation Loss'],
    ascending=[False, True]
    )['Batch Normalization Present'].iloc[0]

print(f"Batch Normalization present for best case: {best_do_batch}")
```

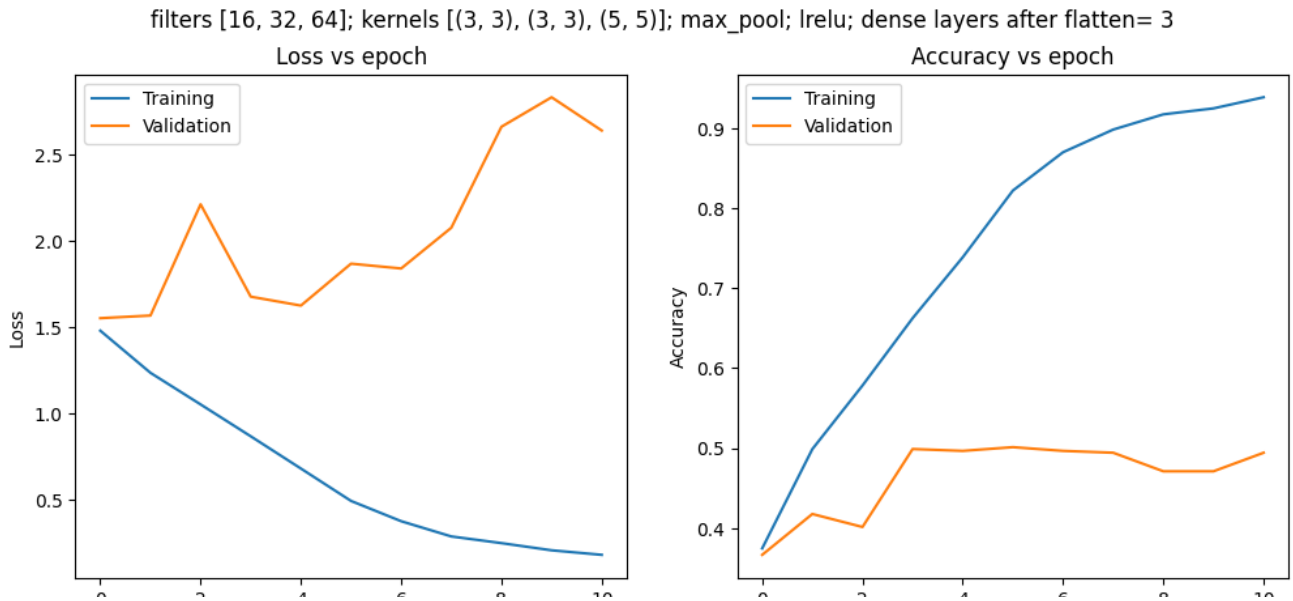
```
 best dropout rate: 0.1
 Batch Normalization present for best case: True
```

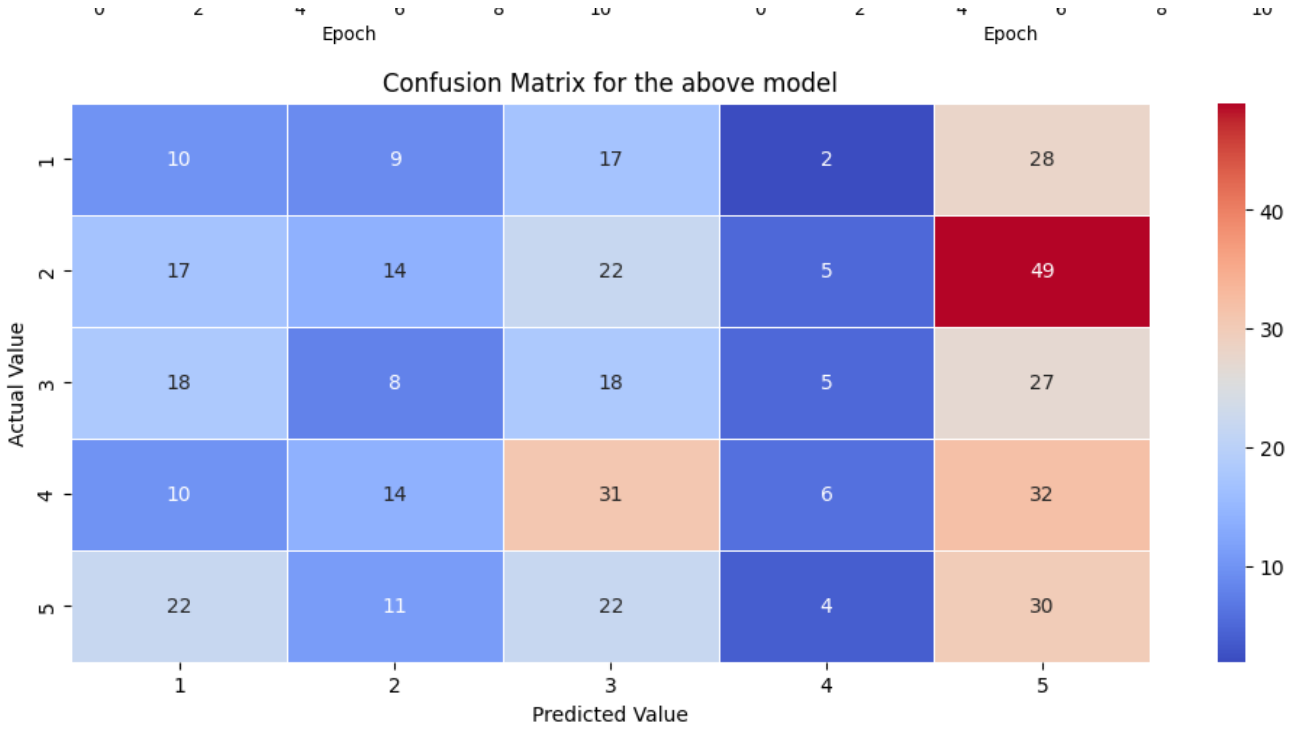
Task 4.6

For the best set of parameters from the above runs, add [1,2,3] more convolution layers, and compare the size of trainable parameters and also compare the time required to train each model for 10 epoch.

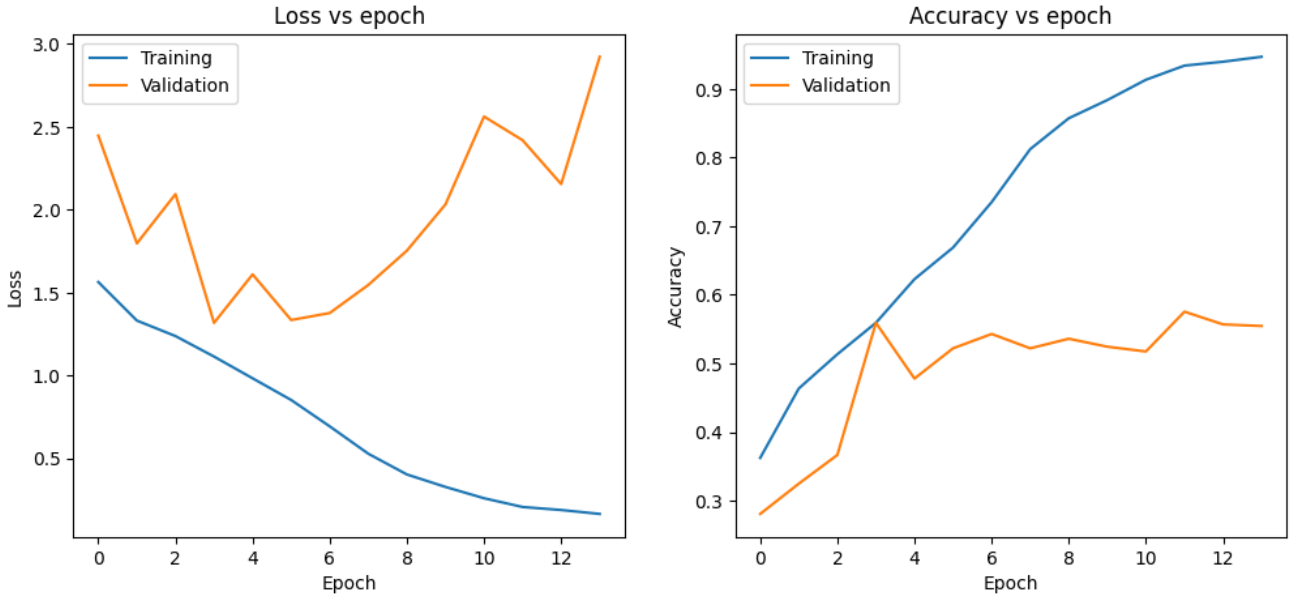
```
import time

result = pd.DataFrame(columns=[
    'Convolution kernel_size',
    'Convolution filters size',
    'Pooling Layers',
    'Activation',
    'FC layer (after Flatten)',
    'Dropout Rate',
    'Batch Normalization Present',
    'Extra Conv Layers',
    'Validation Loss',
    'Validation Accuracy',
    'Validation Precision',
    'Validation Recall',
    'Time Taken'
])

convolution_filters = [16, 32, 64]
extra_conv_layers = [0, 1, 2, 3]

for extra_conv_layer in extra_conv_layers:
    # making a deep copy to avoid editing of original element
    convolution_filters_copy = []
    best_conv_kernel_copy = []

    for filtr, kernel in zip(convolution_filters, best_conv_kernel):
        convolution_filters_copy.append(filtr)
        best_conv_kernel_copy.append(kernel)
```

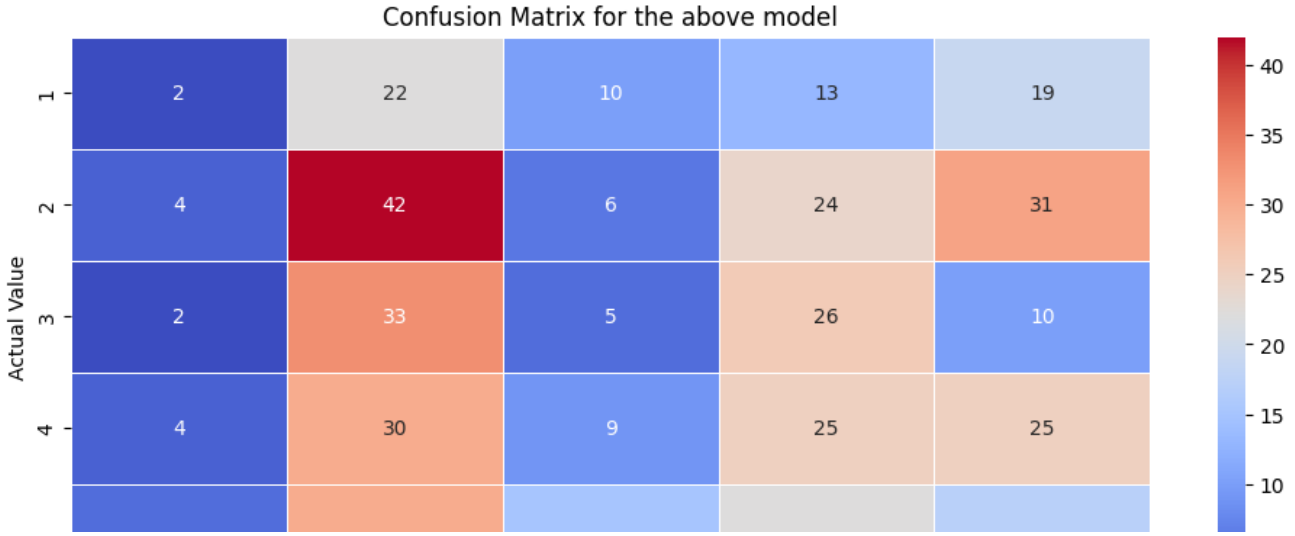
```
start_time = time.time()

val_loss, val_acc, val_precision, val_recall = train_model(
    drop_rate=best_dropout,
    conv_kernels=best_conv_kernel_copy,
    conv_filters=convolution_filters_copy,
    activation=best_activation,
    pool=best_pool,
    add_batch_norm=best_do_batch,
    num_fc_layers=best_num_fc_layers,
    extra_conv_layers=extra_conv_layer,
    train_dataset=train_dataset,
    val_dataset=val_dataset,
)
end_time = time.time()

time_taken = end_time - start_time

result.loc[len(result.index)] = [
    best_conv_kernel_copy,
    convolution_filters_copy,
    best_pool,
    best_activation,
    best_num_fc_layers,
    best_dropout,
    best_do_batch,
    extra_conv_layer,
    val_loss,
    val_acc,
    val_precision,
    val_recall,
    time_taken
]
```

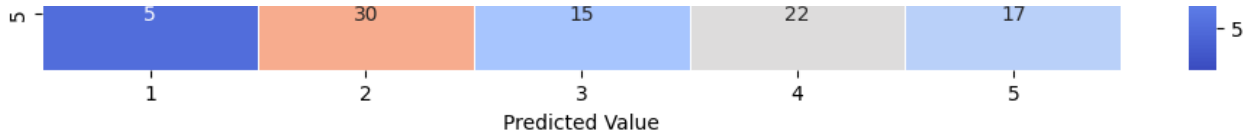




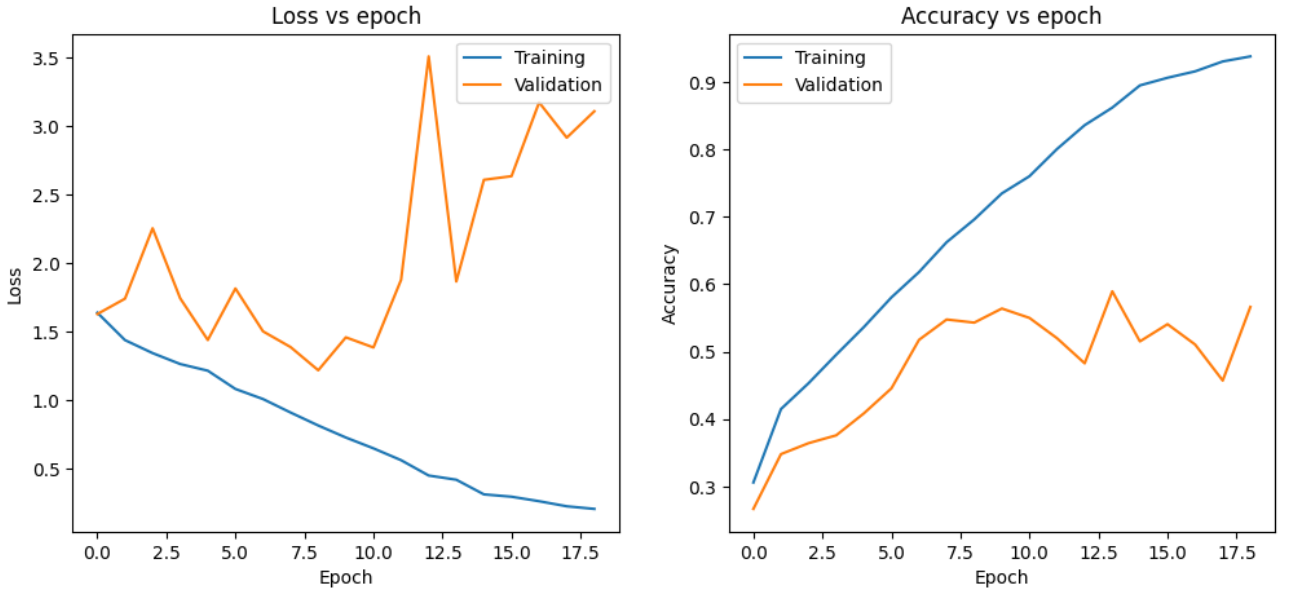
filters [16, 32, 64, 128]; kernels [(3, 3), (3, 3), (5, 5), (5, 5)]; max_pool; lrelu; dense layers after flatten= 3

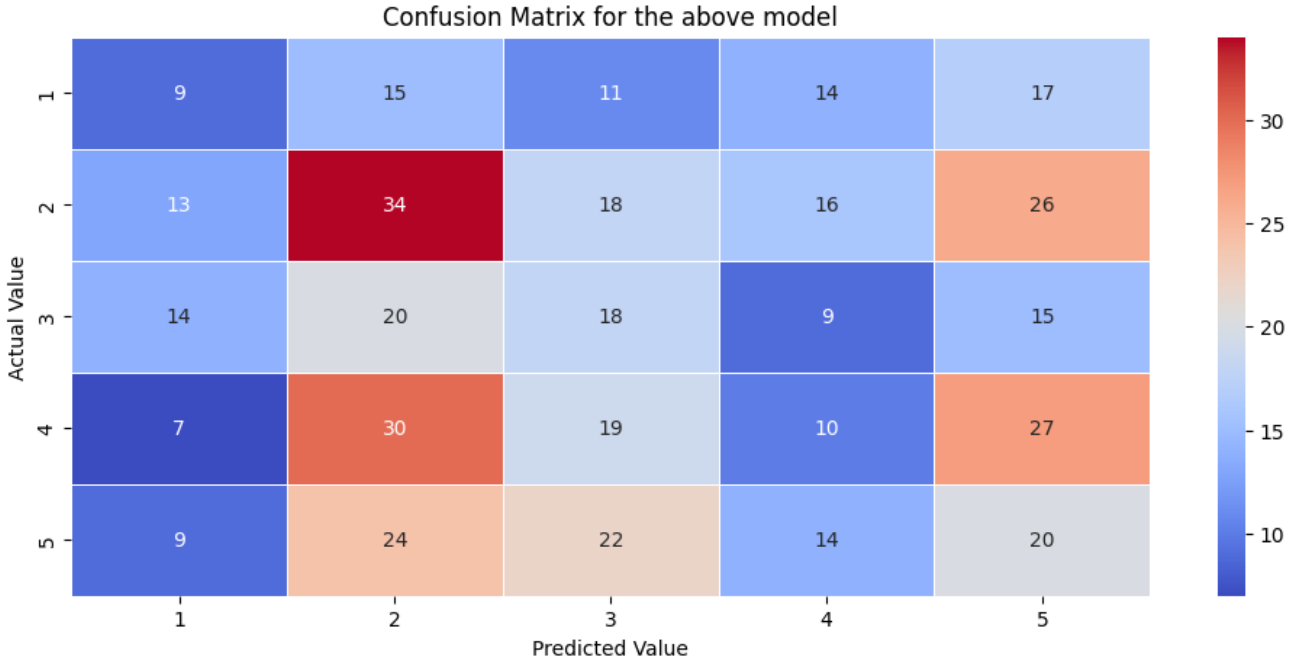




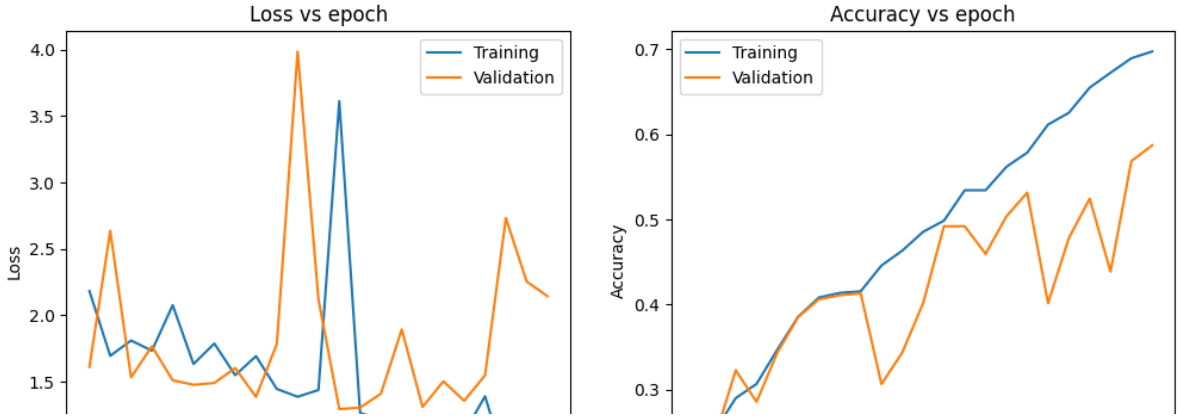


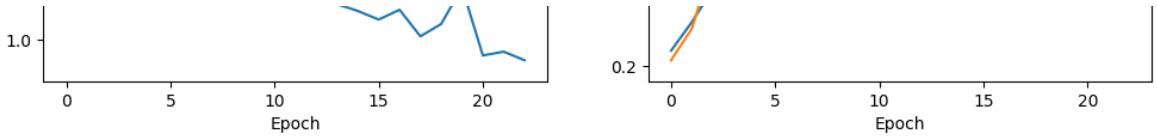
filters [16, 32, 64, 128, 256]; kernels [(3, 3), (3, 3), (5, 5), (5, 5), (5, 5)]; max_pool; lrelu; dense layers after flatten= 3

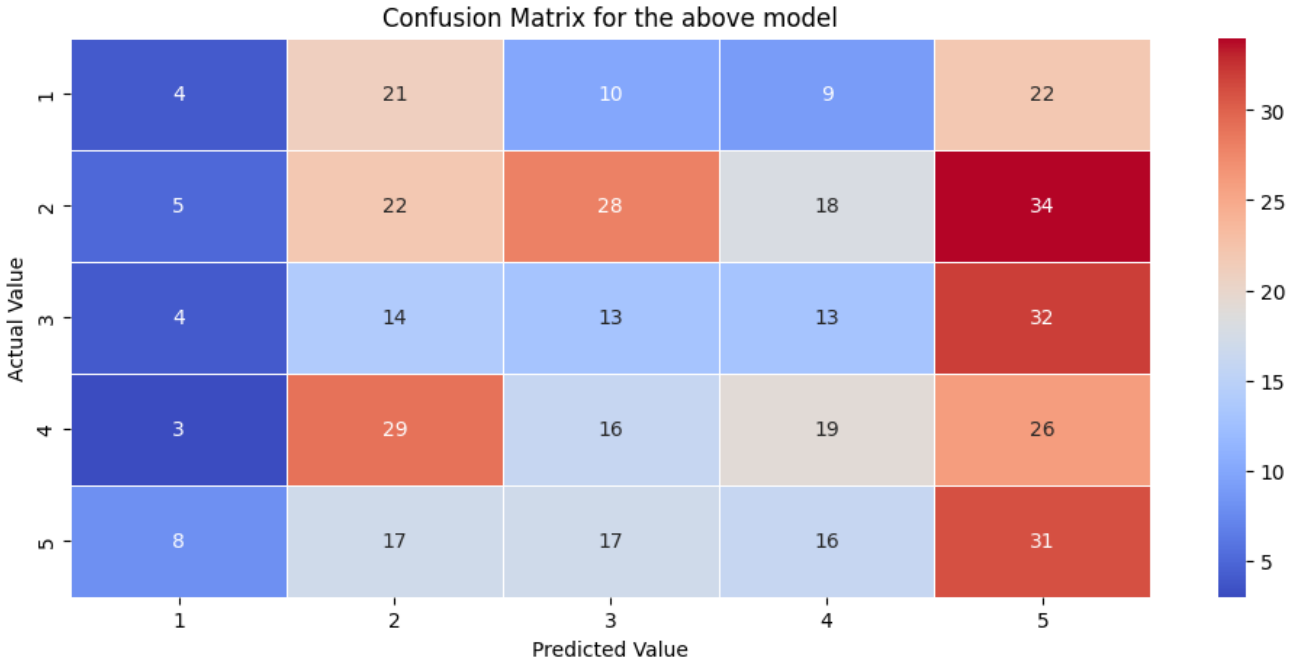




filters [16, 32, 64, 128, 256, 512]; kernels [(3, 3), (3, 3), (5, 5), (5, 5), (5, 5), (5, 5)]; max_pool; lrelu; dense layers after flatten= 3




1.0
0
5
10
15
20
Epoch
0.2
0
5
10
15
20
Epoch

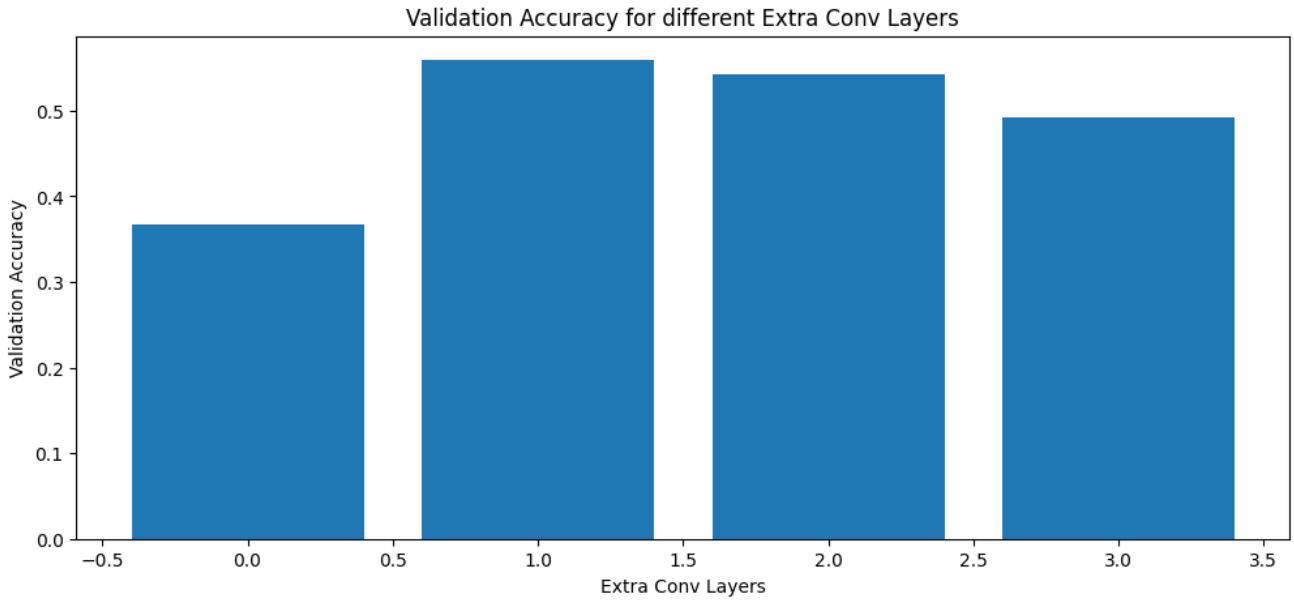

Confusion Matrix for the above model
Actual Value
1
2
3
4
5
4 21 10 9 22
5 22 28 18 34
4 14 13 13 32
3 29 16 19 26
8 17 17 16 31
1
2
3
4
5
Predicted Value
30
25
20
15
10
5

```
result['Validation f1'] = \
    2*result['Validation Precision']*result['Validation Recall']/(result['Validation Prec
result
```

	Convolution kernel_size	Convolution filters size	Pooling Layers	Activation	FC layer (after Flatten)	Dropout Rate	Batch Normalization Present	L
0	[(3, 3), (3, 3), (5, 5)]	[16, 32, 64]	max	lrelu	3	0.1	True	
1	[(3, 3), (3, 3), (5, 5), (5, 5)]	[16, 32, 64, 128]	max	lrelu	3	0.1	True	

2	[(3, 3), (3, 3), (5, 5), (5, 5), (5, 5)]	[16, 32, 64, 128, 256]	max	lrelu	3	0.1	True
3	[(3, 3), (3, 3), (5, 5), (5, 5), (5, 5), (5, 5)]	[16, 32, 64, 128, 256, 512]	max	lrelu	3	0.1	True

```
plt.figure(figsize=(12, 5))
plt.bar(
    result['Extra Conv Layers'],
    result['Validation Accuracy'])
plt.ylabel('Validation Accuracy')
plt.xlabel('Extra Conv Layers')
plt.title("Validation Accuracy for different Extra Conv Layers")
plt.show()
```




```
best_extra_conv_layer = result.sort_values(
    by=['Validation Accuracy', 'Validation Loss'],
    ascending=[False, True]
    )['Extra Conv Layers'].iloc[0]

best_extra_conv_layer
```

```
1
```

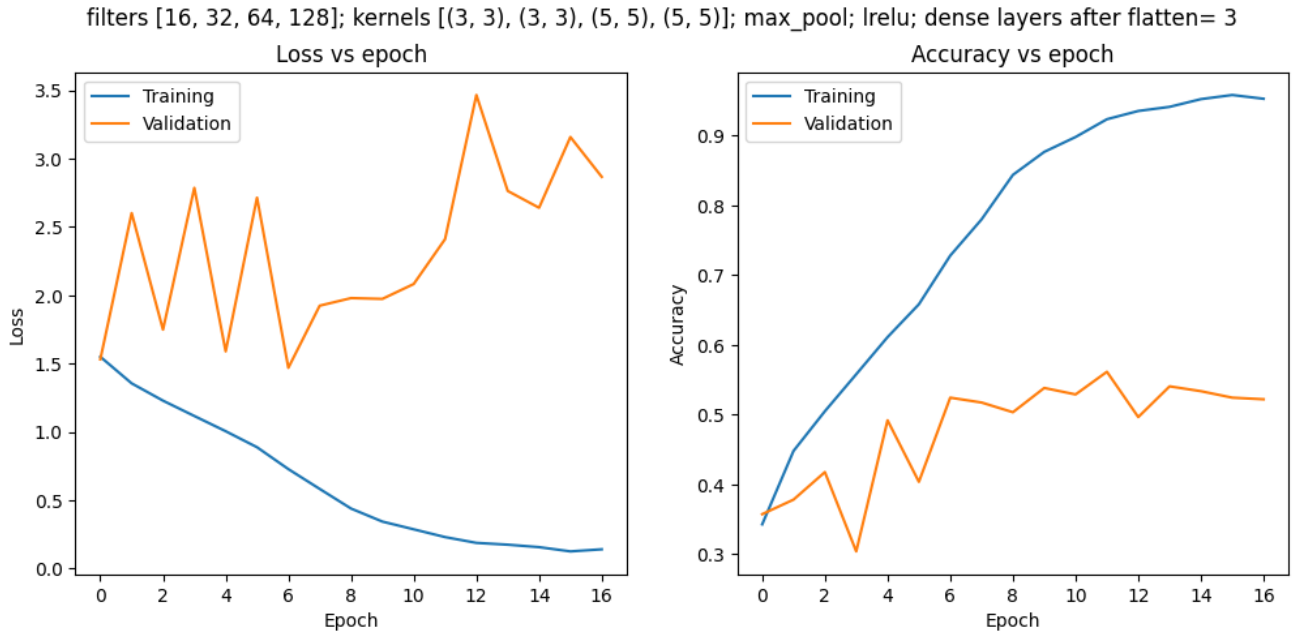
Task 4.7

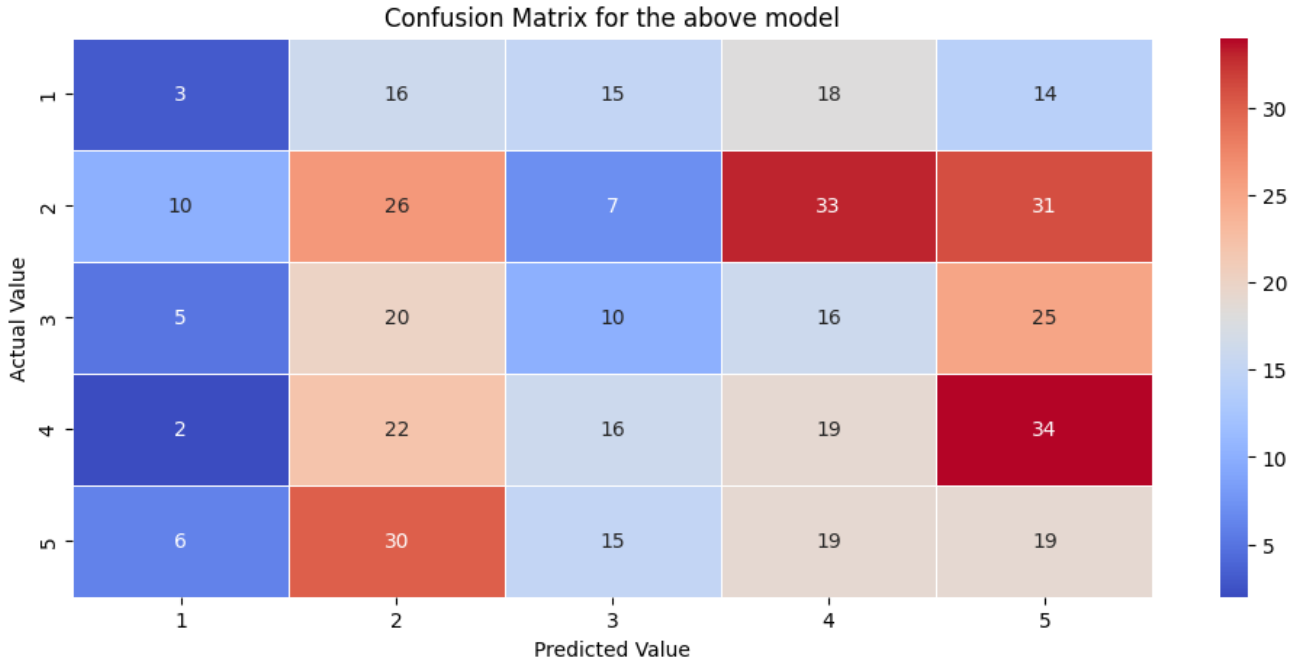
For the best set of parameters obtained here repeat the experimentation for color images. And visualize the test result.

```
result = pd.DataFrame(columns=[
    'Convolution kernel_size',
    'Convolution filters size',
    'Pooling Layers',
    'Activation',
    'FC layer (after Flatten)',
    'Dropout Rate',
    'Batch Normalization Present',
    'Extra Conv Layers',
    'Color Mode',
    'Validation Loss',
    'Validation Accuracy',
    'Validation Precision',
    'Validation Recall',
])

convolution_filters = [16, 32, 64]

val_loss, val_acc, val_precision, val_recall = train_model(
    drop_rate=best_dropout,
    conv_kernels=best_conv_kernel,
    conv_filters=convolution_filters,
    activation=best_activation,
    pool=best_pool,
    add_batch_norm=best_do_batch,
    num_fc_layers=best_num_fc_layers,
    extra_conv_layers=best_extra_conv_layer,
    train_dataset=train_dataset,
    val_dataset=val_dataset
)

result.loc[len(result.index)] = [
    best_conv_kernel,
    convolution_filters,
    best_pool,
    best_activation,
    best_num_fc_layers,
    best_dropout,
    best_do_batch,
    best_extra_conv_layer,
    'grayscale',
    val_loss,
```

```
    val_acc,
    val_precision,
    val_recall

]

convolution_filters = [16, 32, 64]

color_train_dataset = tf.keras.preprocessing.image_dataset_from_directory(
    directory=DATASET_DIRECTORY_PATH,
    labels="inferred",
    label_mode="categorical",  # output of model will be softmax categorical
    color_mode="rgb",
    batch_size=32,
    image_size=(80, 80),
    shuffle=True,
    seed=seed,  # same seed for both dataset so that no overlap happens
    validation_split=0.1,  # 90:10 split
    subset='training',
    crop_to_aspect_ratio=False,
)

color_val_dataset = tf.keras.preprocessing.image_dataset_from_directory(
    directory=DATASET_DIRECTORY_PATH,
    labels="inferred",
    label_mode="categorical",  # output of model will be softmax categorical
    color_mode="rgb",
    batch_size=32,
    image_size=(80, 80),
    shuffle=True,
    seed=seed,
    validation_split=0.1,  # 90:10 split
    subset='validation',
    crop_to_aspect_ratio=False,
)

val_loss, val_acc, val_precision, val_recall = train_model(
    drop_rate=best_dropout,
    conv_kernels=best_conv_kernel,
    conv_filters=convolution_filters,
    activation=best_activation,
    pool=best_pool,
    add_batch_norm=best_do_batch,
    num_fc_layers=best_num_fc_layers,
    extra_conv_layers=best_extra_conv_layer,
    train_dataset=train_dataset,
    val_dataset=val_dataset
)

result.loc[len(result.index)] = [
```

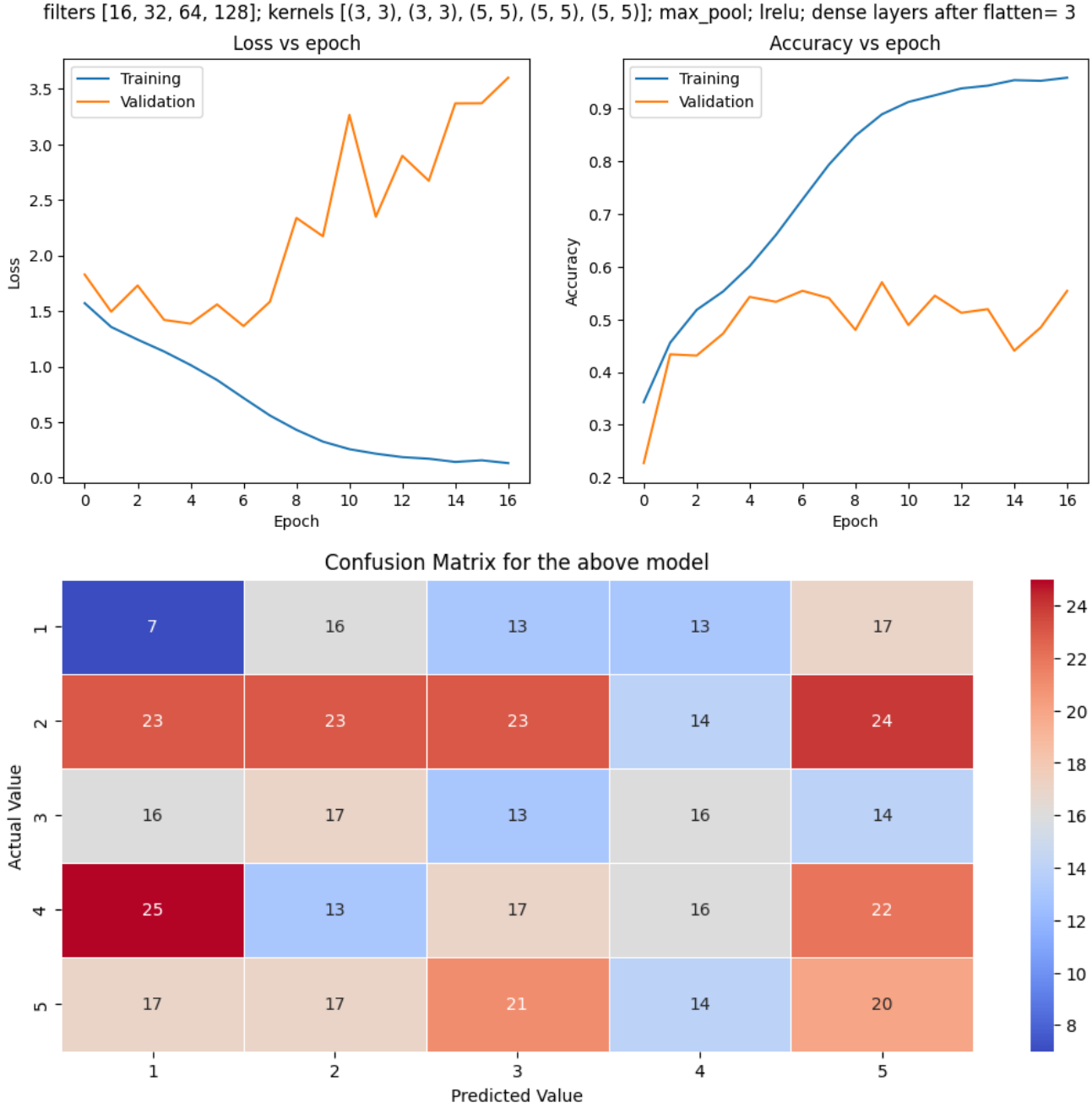
```
    best_conv_kernel,
    convolution_filters,
    best_pool,
    best_activation,
    best_num_fc_layers,
    best_dropout,
    best_do_batch,
    best_extra_conv_layer,
    'rgb',
    val_loss,
    val_acc,
    val_precision,
    val_recall
]
```





Found 4317 files belonging to 5 classes.

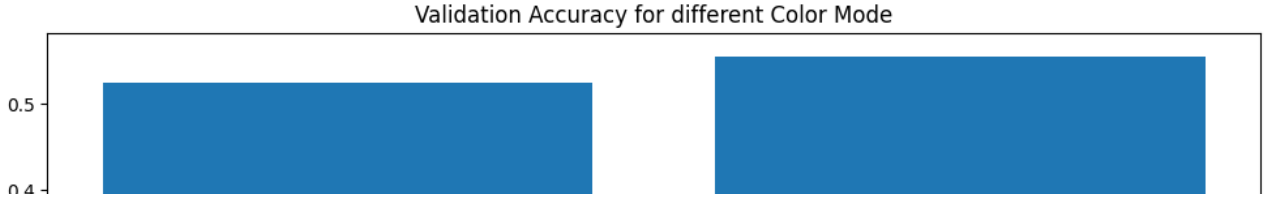
```
Found 4317 files belonging to 5 classes.
Using 3886 files for training.
Found 4317 files belonging to 5 classes.
Using 431 files for validation.
```

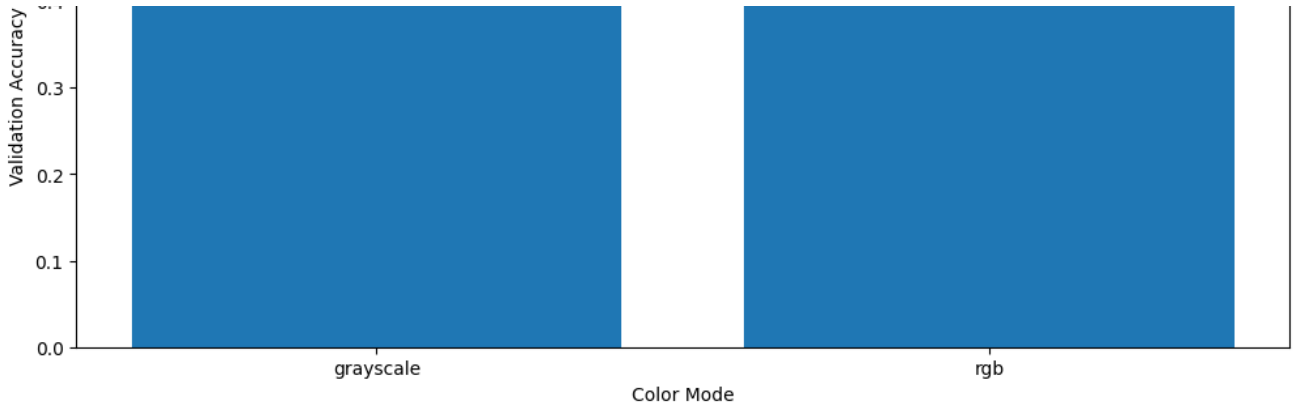


```
result['Validation f1'] = \
    2*result['Validation Precision']*result['Validation Recall']/(result['Validation Prec
result
```

	Convolution kernel_size	Convolution filters size	Pooling Layers	Activation	FC layer (after Flatten)	Dropout Rate	Batch Normalization Present	L
0	[(3, 3), (3, 3), (5, 5), (5, 5), (5, 5)]	[16, 32, 64, 128]	max	lrelu	3	0.1	True	
1	[(3, 3), (3, 3), (5, 5), (5, 5), (5, 5)]	[16, 32, 64, 128]	max	lrelu	3	0.1	True	

```
plt.figure(figsize=(12, 5))
plt.bar(
    result['Color Mode'],
    result['Validation Accuracy'])
plt.ylabel('Validation Accuracy')
plt.xlabel('Color Mode')
plt.title("Validation Accuracy for different Color Mode")
plt.show()
```





Task 5

Plot the graph for the loss vs epoch and accuracy(train, test set) vs epoch for all the above cases. Also, plot the accuracy for all experimentation in a bar graph along with the confusion matrix and F1 score

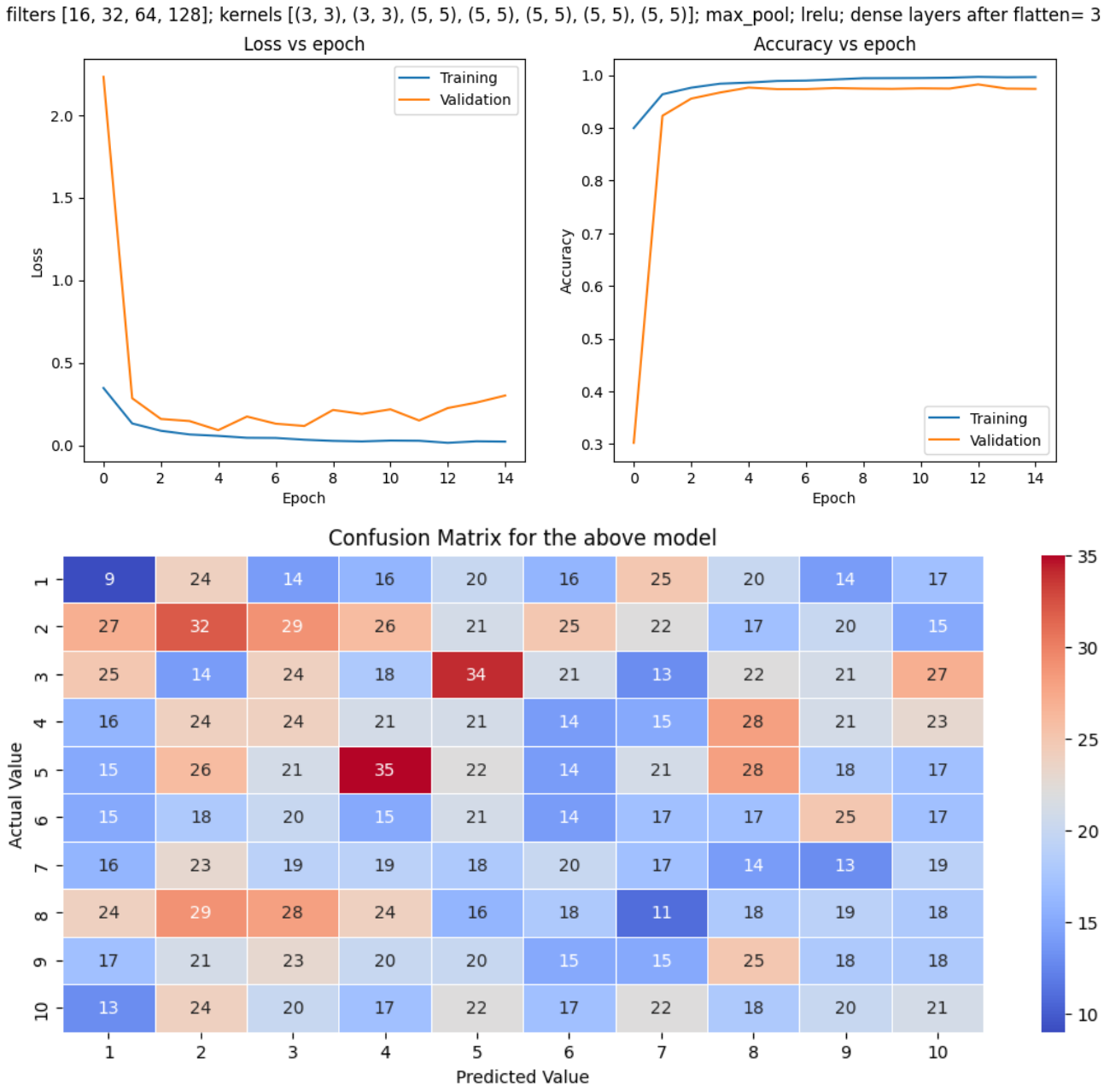
Task 6

For the best model on the MINST dataset in Assignment 5, train a model with MNIST data using the best set of parameters obtained in Question 4. Compare the test accuracy and also the self-created images.

```
import numpy as np
import tensorflow as tf

def create_dataset(X, Y, batch_size=32):
  """ Create train and test TF dataset from X and Y
    The prefetch overlays the preprocessing and model execution of a training step.
    While the model is executing training step s, the input pipeline is reading the data
    AUTOTUNE automatically tune the number for sample which are prefeteched automatically

    Keyword arguments:
    X -- numpy array
    Y -- numpy array
    batch_size -- integer
  """
```

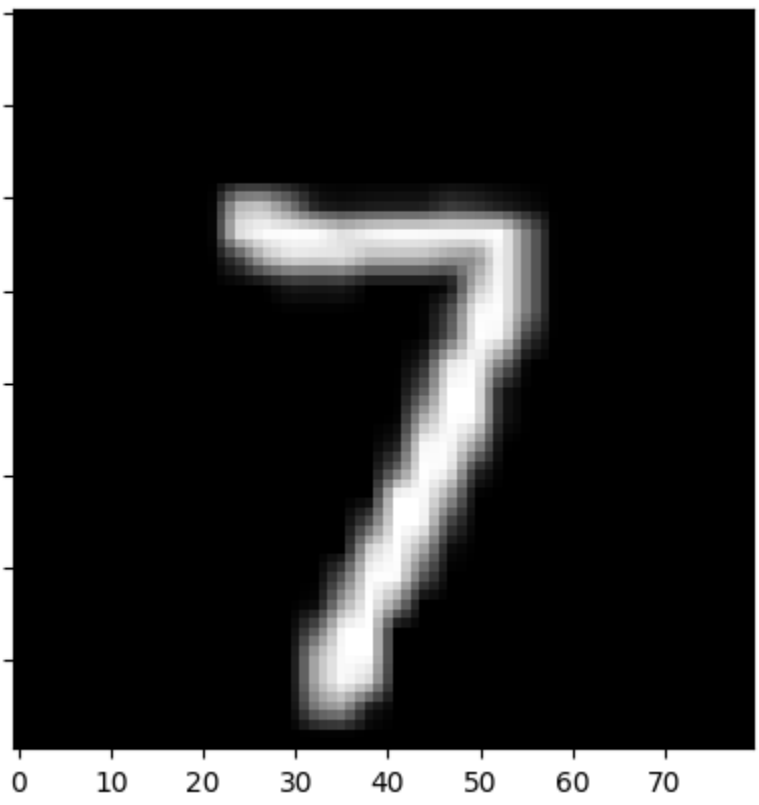
```
  AUTOTUNE = tf.data.experimental.AUTOTUNE

  dataset = tf.data.Dataset.from_tensor_slices((X, Y))
  dataset = dataset.shuffle(buffer_size=1000, reshuffle_each_iteration=True)
  dataset = dataset.batch(batch_size).prefetch(AUTOTUNE)

  return dataset

import pandas as pd
from tensorflow.image import resize

mnist_data = tf.keras.datasets.mnist.load_data()
(x_train, y_train), (x_test, y_test) = mnist_data

#taking less data due to memory limitation
x_train = x_train[0:10000]
x_test = x_test[0:2000]
y_train = y_train[0:10000]
y_test = y_test[0:2000]

#resizing to 80x80 and mapping 0-255 to 0-1
x_train = np.reshape(x_train, (-1, 28, 28, 1))
x_train = x_train/255
x_train = resize(x_train, (80,80))


x_test = np.reshape(x_test, (-1, 28, 28, 1))
x_test = x_test/255
x_test = resize(x_test, (80,80))

y_train = pd.get_dummies(y_train).to_numpy()
y_test = pd.get_dummies(y_test).to_numpy()

mnist_train_dataset=create_dataset(x_train, y_train)
mnist_val_dataset=create_dataset(x_test, y_test)


convolution_filters = [16, 32, 64]
num_class = 10

val_loss, val_acc, val_precision, val_recall, model = train_model(
    drop_rate=best_dropout,
    conv_kernels=best_conv_kernel,
    conv_filters=convolution_filters,
    activation=best_activation,
    pool=best_pool,
    add_batch_norm=best_do_batch,
    num_fc_layers=best_num_fc_layers,
    extra_conv_layers=best_extra_conv_layer,
    train_dataset=mnist_train_dataset,
```

```
    val_dataset=mnist_val_dataset,
    give_model=True
)

print(f"val_loss= {val_loss}\nval_acc={val_acc}\nval_precision={val_precision}\nval_recal
```

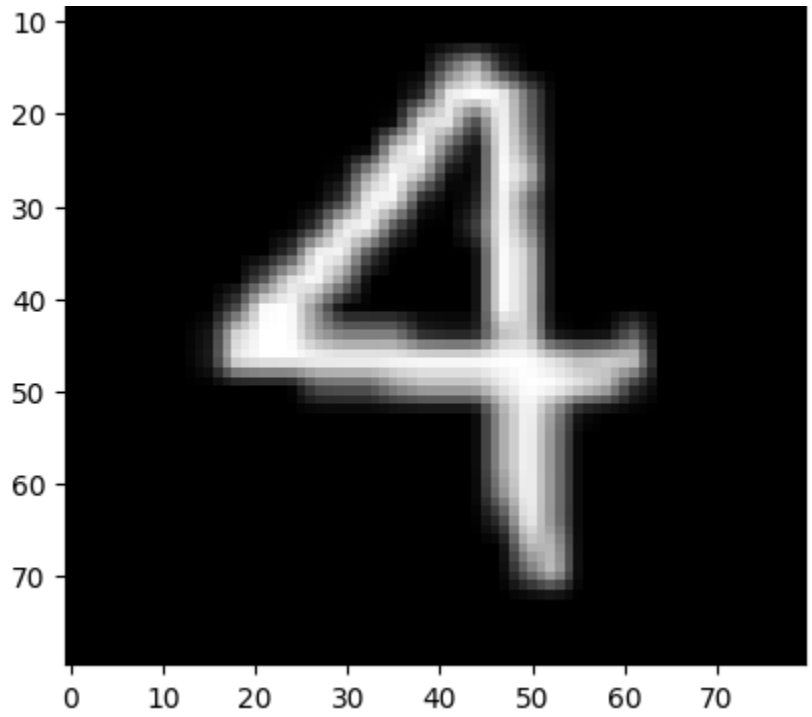



```
val_loss= 0.09174732118844986
val_acc=0.9764999747276306
val_precision=0.977477490901947
val_recall=0.9764999747276306
```

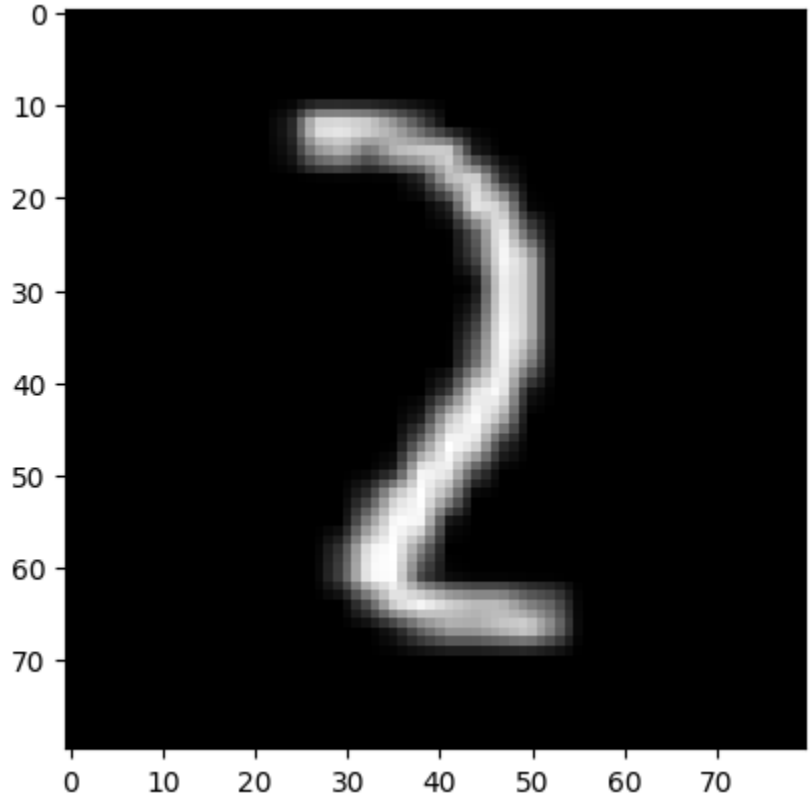
```
import random

random_idx = random.sample(range(0, len(x_test)), 10)

img_to_predict = np.array([x_test[idx] for idx in random_idx])

categorical_predictions = model.predict(img_to_predict)

for img, cat_pred in zip(img_to_predict, categorical_predictions):
    plt.imshow(img, cmap='gray')
    plt.show()
    pred = np.argmax(cat_pred)
    print(f"predict = {pred}")
```



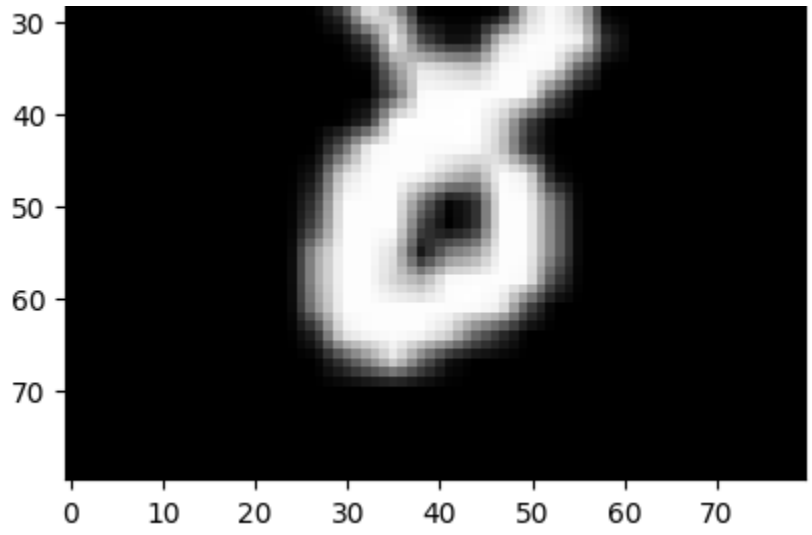

```
predict = 7
```



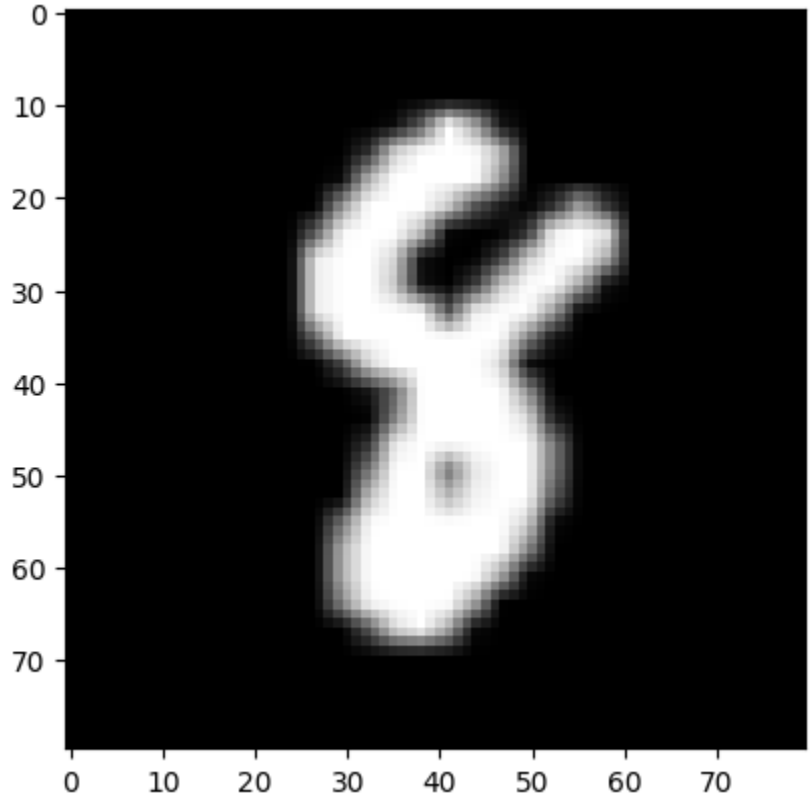
```
predict = 4
```



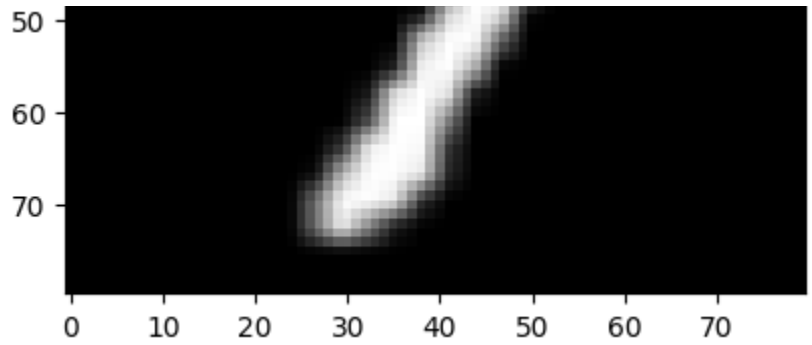
```
predict = 2
```



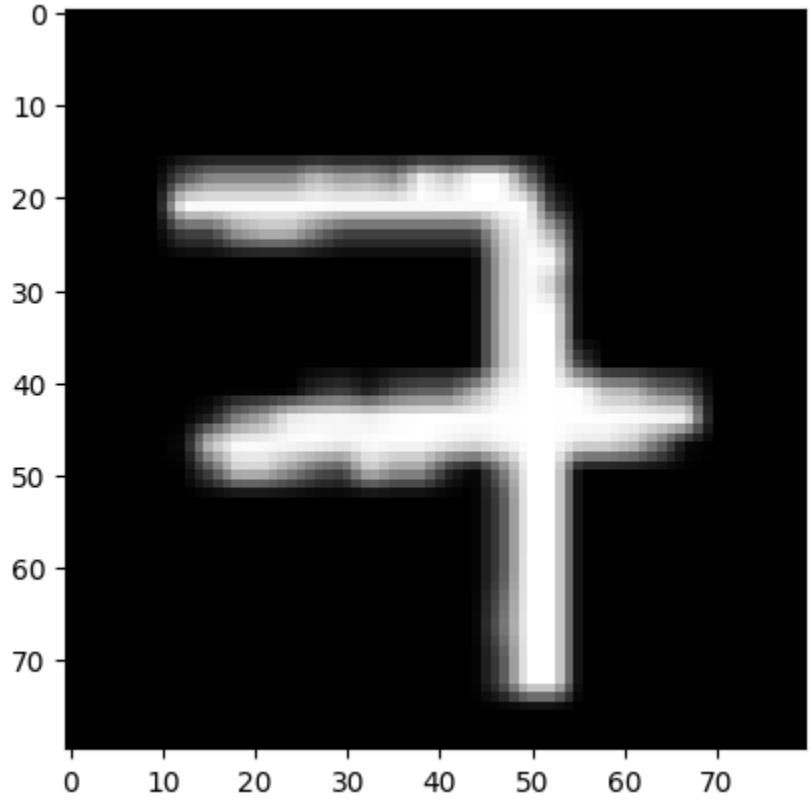

```
predict = 8
```



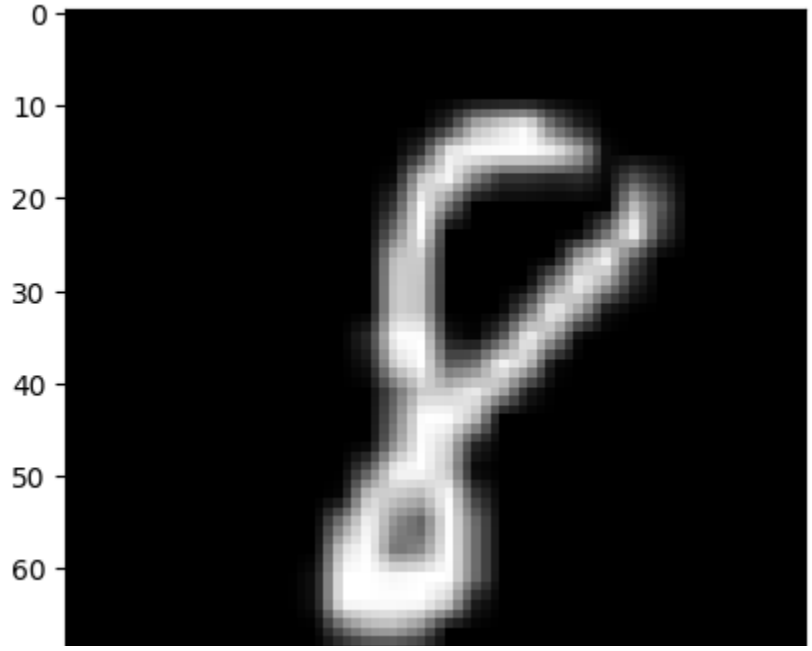

```
predict = 8
```

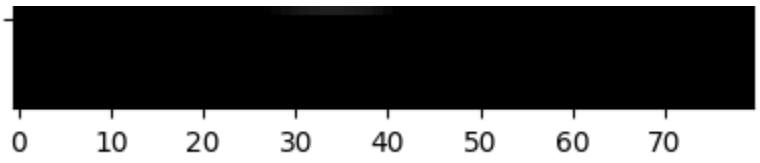



```
predict = 9
```

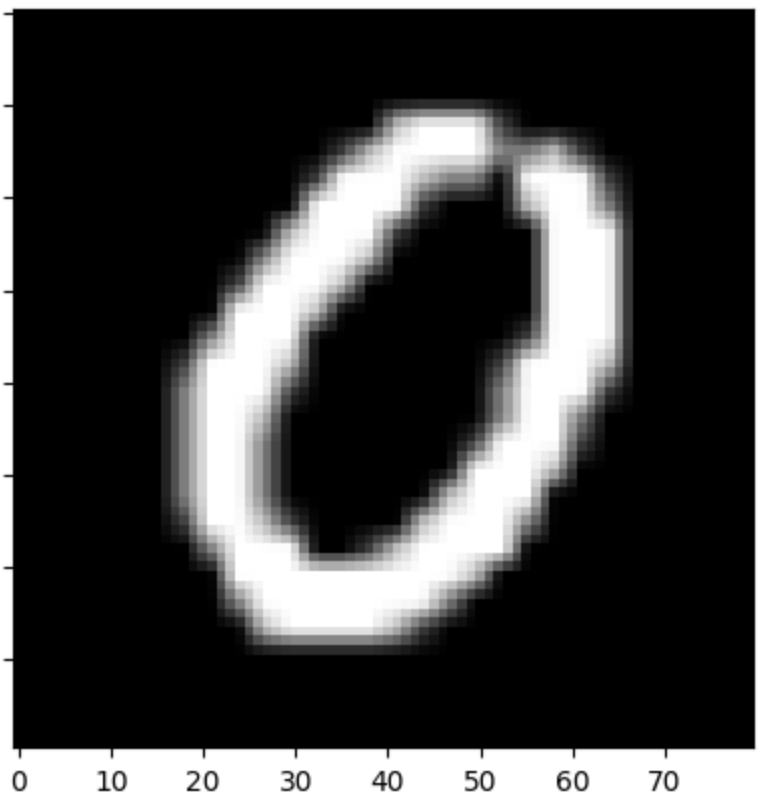



```
predict = 7
```

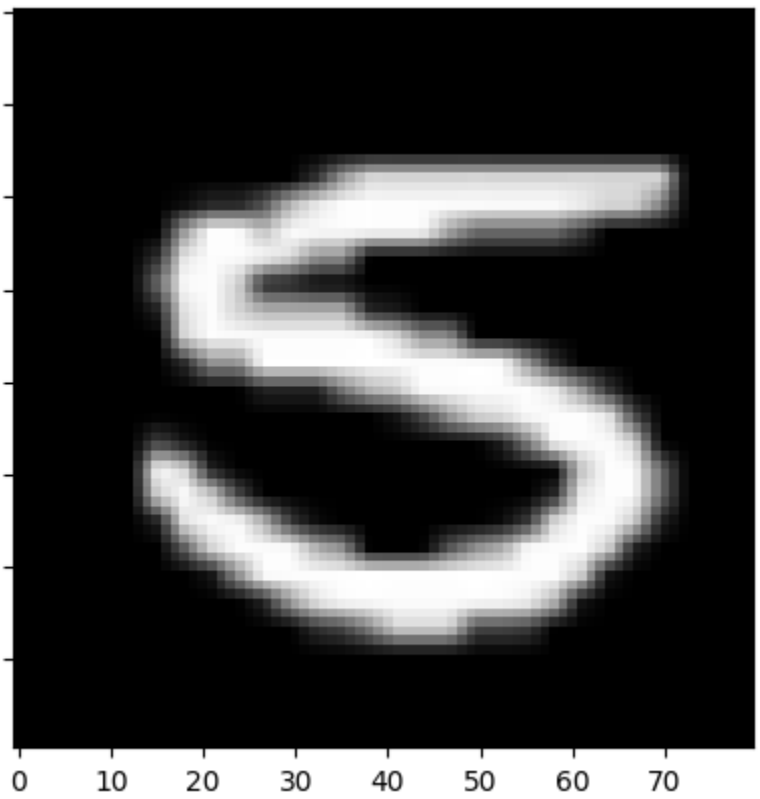





```
predict = 8
```




```
predict = 0
```



```
predict = 5
```