

3c

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## 0.1 CSc 84020 Neural Networks and Deep Learning, Spring 2021

### Homework 2 (3c)

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## 0.2 Import Libraries & Load Data

Import libraries and define classes

```
[ ]: from google.colab import drive
import glob
import os
import numpy as np
import time
import random as rn
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from itertools import cycle
import pylab
from sklearn.model_selection import train_test_split
from sklearn.metrics import roc_curve, auc, roc_auc_score, \
    ↪precision_recall_curve
from sklearn.metrics import classification_report as cr
from sklearn.metrics import confusion_matrix as cm
import tensorflow as tf
from tensorflow.keras.callbacks import Callback
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Input, Dense, BatchNormalization, Dropout, \
    ↪LeakyReLU
from tensorflow.keras.regularizers import L2
from tensorflow.keras.initializers import GlorotNormal
from tensorflow.keras.optimizers import SGD, Adam
from tensorflow.keras.utils import to_categorical, plot_model

print(tf.__version__)
```

### 2.4.1

```
[ ]: drive.mount('/content/drive')
```

Mounted at /content/drive

```
[ ]: start_total_time = time.time()
```

```
[ ]: # Different options for classes: selection to be set with constants

# critters (6 classes)
critters = ['ant', 'bee', 'butterfly', 'mosquito', 'scorpion',
            'spider']

# birds (6 classes)
birds = ['bird', 'duck', 'flamingo', 'owl', 'parrot',
         'penguin']

# ocean animals (8 classes)
ocean_animals = ['crab', 'dolphin', 'fish', 'lobster', 'octopus',
                 'sea%20turtle', 'shark', 'whale']

# land mammals (22 classes)
land_mammals = ['bear', 'camel', 'cat', 'cow', 'dog',
                'elephant', 'giraffe', 'hedgehog', 'horse', 'kangaroo',
                'lion', 'monkey', 'mouse', 'panda', 'pig',
                'rabbit', 'raccoon', 'rhinoceros', 'sheep', 'squirrel',
                'tiger', 'zebra']

# all animals (47 classes)
all_animals = ['ant', 'bat', 'bear', 'bee', 'bird',
               'butterfly', 'camel', 'cat', 'cow', 'crab',
               'crocodile', 'dog', 'dolphin', 'duck', 'elephant',
               'fish', 'flamingo', 'frog', 'giraffe', 'hedgehog',
               'horse', 'kangaroo', 'lion', 'lobster', 'monkey',
               'mosquito', 'mouse', 'octopus', 'owl', 'panda',
               'parrot', 'penguin', 'pig', 'rabbit', 'raccoon',
               'rhinoceros', 'scorpion', 'sea%20turtle', 'shark', 'sheep',
               'snail', 'snake', 'spider', 'squirrel', 'tiger',
               'whale', 'zebra']
```

#### Set constants

```
[ ]: classes = critters
CLASS_SAMPLE_MAX = 25000
DATA_DIR = '/content/drive/My Drive/Colab Notebooks/NN DL/HW2/data/'
```

## Load data

```
[ ]: def load_bitmaps(data_dir=DATA_DIR, class_sample_max=CLASS_SAMPLE_MAX):
    class_files = []
    for c in classes:
        print(c, end=' ')
        class_files.append(os.path.join(DATA_DIR, c + '.npy'))
    class_files.sort()

    X = np.empty([0,784])
    y = np.empty([0])

    print()
    for id, class_file in enumerate(class_files):
        print(id, end=' ')
        loaded_data = np.load(class_file)
        loaded_data = loaded_data[0:CLASS_SAMPLE_MAX, :]
        labels = np.full(loaded_data.shape[0],id)

        X = np.concatenate((X, loaded_data), axis = 0)
        y = np.append(y, labels)

    return X, y
```

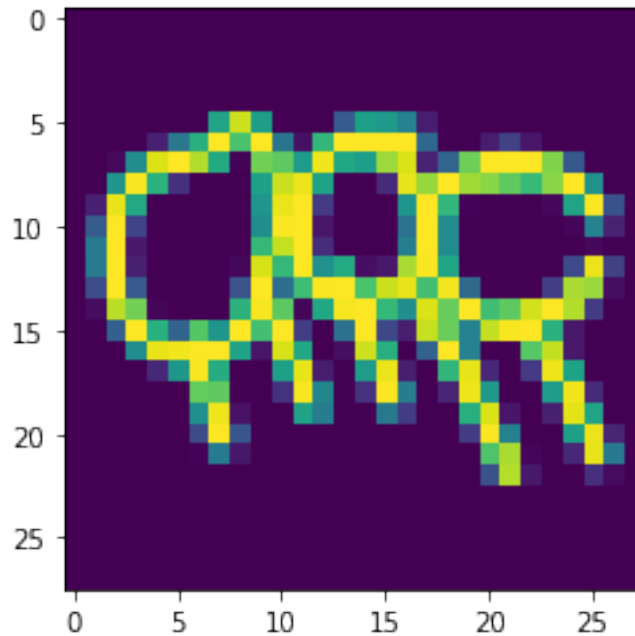
```
[ ]: start = time.time()
X, y = load_bitmaps()
print(f'\nLoading time: %.3f' % int(time.time() - start), 'seconds')
print(y[-CLASS_SAMPLE_MAX-5:-CLASS_SAMPLE_MAX+5])
```

```
ant bee butterfly mosquito scorpion spider
0 1 2 3 4 5
Loading time: 12.000 seconds
[4. 4. 4. 4. 5. 5. 5. 5. 5.]
```

## Data example

```
[ ]: id = 20000
plt.imshow(X[id].reshape(28,28))
print(classes[int(y[id].item())])
```

ant



```
[ ]: x[20000]
```

```
[ ]: array([0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,  
0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,  
0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,  
0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,  
0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,  
0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,  
0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,  
0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,  
0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,  
0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,  
0., 0., 0., 0., 149., 236., 142., 0., 0., 0., 73.,  
144., 137., 113., 21., 0., 0., 0., 0., 0., 0., 0.,  
0., 0., 0., 0., 0., 0., 0., 22., 101., 160., 255.,  
182., 255., 99., 11., 169., 255., 255., 255., 255., 86., 0.,  
0., 19., 49., 15., 0., 0., 0., 0., 0., 0., 0.,  
6., 125., 242., 255., 226., 155., 2., 201., 192., 141., 250.,  
153., 143., 218., 241., 25., 83., 199., 255., 255., 255., 207.,  
70., 0., 0., 0., 0., 0., 133., 253., 163., 35., 0.,  
0., 0., 146., 235., 248., 147., 0., 0., 30., 246., 216.,  
255., 219., 210., 193., 172., 210., 255., 129., 0., 0., 0.,  
23., 247., 154., 0., 0., 0., 0., 0., 133., 248., 255.]
```

[illegible]

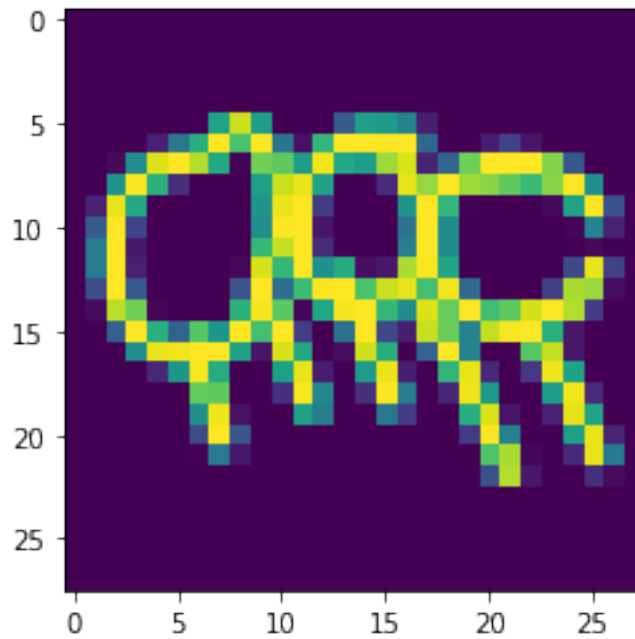
### 0.3 Normalization

```
[ ]: # Normalization to range [0, 1]
X = X / 255
```

### Data example after normalization

```
[ ]: id = 20000
plt.imshow(X[id].reshape(28,28))
print(classes[int(y[id].item())])
```

ant



```
[ ]: X[20000]
```

[illegible]

0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.58431373,	0.9254902	, 0.55686275,	
0.	, 0.	, 0.	, 0.28627451,	0.56470588,	
0.5372549	, 0.44313725,	0.08235294,	0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.08627451,	0.39607843,	0.62745098,	
1.	, 0.71372549,	1.	, 0.38823529,	0.04313725,	
0.6627451	, 1.	, 1.	, 1.	, 1.	,
0.3372549	, 0.	, 0.	, 0.0745098	, 0.19215686,	
0.05882353,	0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.02352941,	0.49019608,	
0.94901961,	1.	, 0.88627451,	0.60784314,	0.00784314,	
0.78823529,	0.75294118,	0.55294118,	0.98039216,	0.6	,
0.56078431,	0.85490196,	0.94509804,	0.09803922,	0.3254902	,
0.78039216,	1.	, 1.	, 1.	, 0.81176471,	
0.2745098	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.52156863,	0.99215686,	0.63921569,	0.1372549	,
0.	, 0.	, 0.	, 0.57254902,	0.92156863,	
0.97254902,	0.57647059,	0.	, 0.	, 0.11764706,	
0.96470588,	0.84705882,	1.	, 0.85882353,	0.82352941,	
0.75686275,	0.6745098	, 0.82352941,	1.	, 0.50588235,	
0.	, 0.	, 0.	, 0.09019608,	0.96862745,	
0.60392157,	0.	, 0.	, 0.	, 0.	,
0.	, 0.52156863,	0.97254902,	1.	, 0.16862745,	
0.	, 0.	, 0.	, 0.5254902	, 1.	,

0.6627451 , 0.00784314, 0. , 0. , 0. ,  
 0.01960784, 0.58431373, 0.99607843, 0.25098039, 0. ,  
 0. , 0.29019608, 1. , 0.2 , 0. ,  
 0. , 0. , 0. , 0. , 0.49019608,  
 0.99607843, 1. , 0.05882353, 0. , 0. ,  
 0. , 0.38039216, 1. , 0.48235294, 0. ,  
 0. , 0. , 0. , 0. , 0.01176471,  
 0.44313725, 0.09803922, 0. , 0. , 0.41568627,  
 1. , 0.06666667, 0. , 0. , 0. ,  
 0. , 0. , 0.66666667, 0.91372549, 1. ,  
 0.1254902 , 0. , 0. , 0. , 0.43137255,  
 1. , 0.48235294, 0. , 0. , 0. ,  
 0. , 0. , 0. , 0.01960784, 0. ,  
 0. , 0. , 0.40784314, 1. , 0.08627451,  
 0. , 0. , 0. , 0. , 0.01960784,  
 0.94117647, 0.66666667, 1. , 0.50588235, 0.61568627,  
 0.03921569, 0.06666667, 0.8745098 , 0.99215686, 0.58823529,  
 0. , 0. , 0. , 0. , 0. ,  
 0.22352941, 0.97254902, 0.19215686, 0. , 0. ,  
 0.23529412, 1. , 0.27843137, 0. , 0. ,  
 0. , 0. , 0.25490196, 1. , 0.36078431,  
 0.69019608, 0.99607843, 1. , 0.71764706, 0.92156863,  
 0.96862745, 0.70196078, 0.98431373, 0.34509804, 0. ,  
 0. , 0. , 0.18039216, 0.8745098 , 0.85098039,  
 0.03529412, 0. , 0. , 0.03137255, 0.89803922,  
 0.78823529, 0.01176471, 0. , 0. , 0. ,  
 0.64313725, 0.98823529, 0.74901961, 0.01568627, 0.6 ,  
 0.98823529, 1. , 0.66666667, 0.49019608, 0.94901961,  
 0.76862745, 1. , 0.69411765, 0.75294118, 0.93333333,  
 1. , 0.88627451, 0.17647059, 0. , 0. ,  
 0. , 0. , 0.30588235, 1. , 0.63529412,  
 0.31764706, 0.7372549 , 0.5254902 , 1. , 0.70196078,  
 1. , 0.18039216, 0. , 0.37647059, 1. ,  
 0.21568627, 0.08235294, 0.91372549, 0.77254902, 0.44313725,  
 0.90980392, 0.99215686, 1. , 0.63529412, 0.06666667,  
 0. , 0. , 0. , 0. , 0. ,  
 0. , 0.49019608, 0.96862745, 0.98039216, 1. ,  
 1. , 0.57647059, 0.05882353, 0.94117647, 0.6 ,  
 0. , 0.03529412, 0.9254902 , 0.62745098, 0. ,  
 0.31372549, 1. , 0.44313725, 0. , 0.00392157,  
 0.74117647, 0.90980392, 0.06666667, 0. , 0. ,  
 0. , 0. , 0. , 0. , 0. ,  
 0.10980392, 0.52941176, 0.99215686, 0.61960784, 0. ,  
 0. , 0.56862745, 0.96470588, 0.0745098 , 0. ,  
 0.54901961, 0.97254902, 0.08235294, 0. , 0.65882353,  
 0.96470588, 0.10980392, 0. , 0.16470588, 0.97647059,  
 0.58039216, 0. , 0. , 0. , 0. ,



9

[illegible]

## 0.4 Multi-layer Perceptron Model

## Set constants and parameters

```
[ ]: RANDOM_STATE = 84020

NUM_CLASSES = len(classes)
INPUT_DIM = X.shape[1]

TEST_SIZE = 0.1
VALIDATION_SPLIT = 0.22

VERBOSE = 0          # choose from: [0, 1]
BATCH_SIZE = 128     # choose from: [32, 64, 128]
EPOCHS = 30          # choose from: [30, 40]

[ ]: SGD = SGD(lr=0.01, decay=1e-6, momentum=0.9, nesterov=True)
optimizer = Adam(lr=0.001, epsilon=1e-06)
          # choose from: [sgd, Adam(lr=0.001, epsilon=1e-06)]

activation = LeakyReLU(alpha=0.01) # choose from: 'relu', LeakyReLU(alpha=0.01)

# dropout = 0          # choose from: [0, 0.1, 0.2, 0.4]

# l2_val = 0           # choose from: [0, 0.1, 0.0005]

loss = 'sparse_categorical_crossentropy'

metrics = ['sparse_categorical_accuracy']
```

### Split X and y into train and test sets

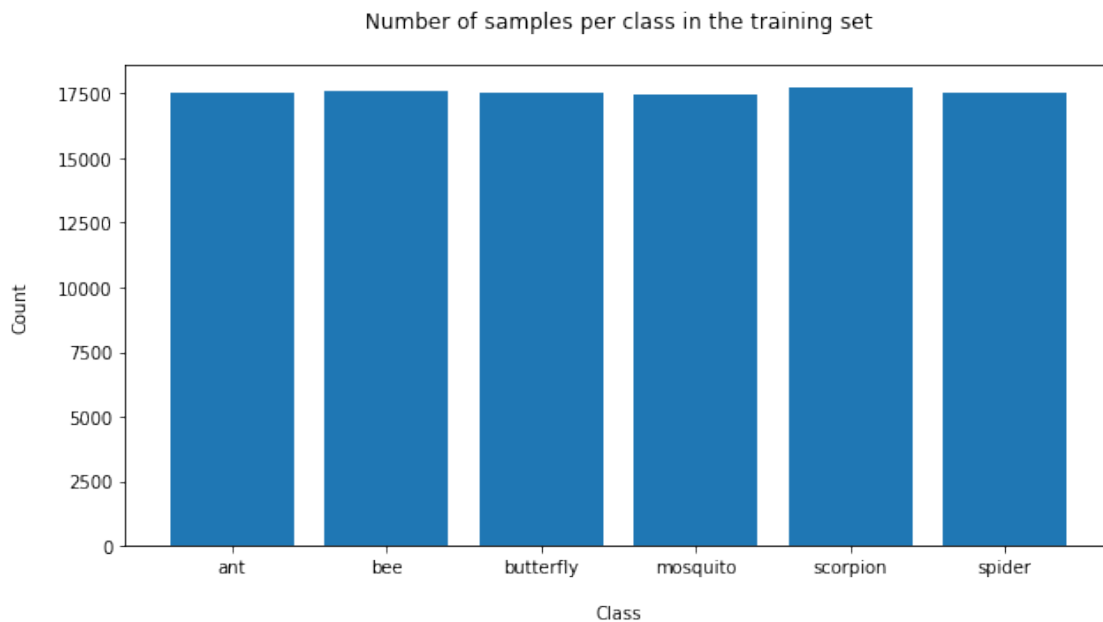
[illegible]

```
[ ]: print('Number of classes:', NUM_CLASSES)
print('Input dimension:', INPUT_DIM)
print('Total dataset \t\tX:\t', X.shape, '\t\tty:\t', y.shape)
print(100 * (1 - TEST_SIZE), '% train \t\tX_train:', X_train.shape,
      '\t\tty_train:', y_train.shape)
print(100 * TEST_SIZE, '% test \t\tX_test:\t', X_test.shape, '\t\tty_test:
      '\t\t', y_test.shape)
```

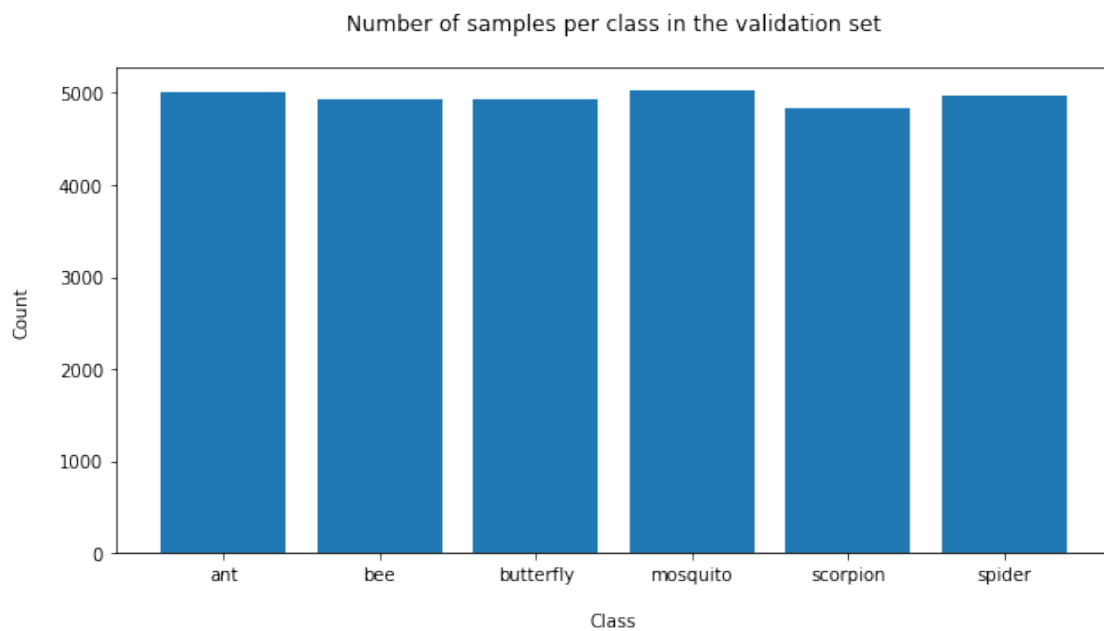
```
Number of classes: 6
Input dimension: 784
Total dataset      X:      (150000, 784)      y:      (150000,)
90.0 % train      X_train: (135000, 784)      y_train: (135000,)
10.0 % test       X_test:  (15000, 784)      y_test:  (15000,)
```

```
[ ]: # Classification: split the dataset into train, validate and test
Xtrain, Xtest, Ytrain, Ytest = train_test_split(X, y, test_size=TEST_SIZE,
      random_state=RANDOM_STATE)
Xtrain, Xval, Ytrain, Yval = train_test_split(Xtrain, Ytrain,
      test_size=VALIDATION_SPLIT, random_state=RANDOM_STATE)
```

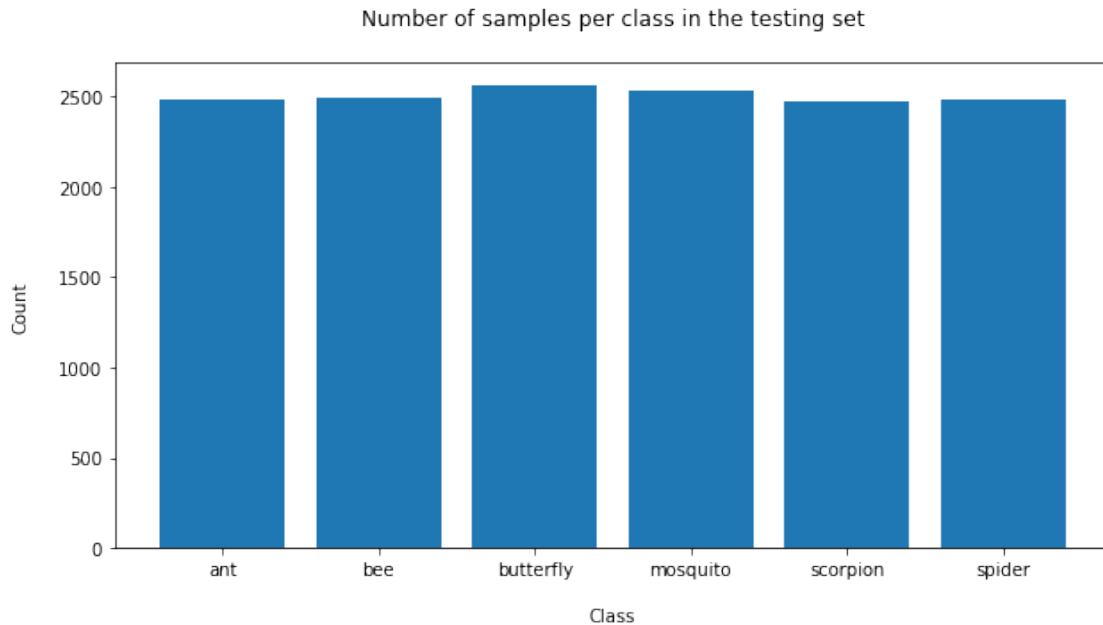
```
[ ]: # Training data
unique, counts = np.unique(Ytrain, return_counts=True)
pylab.rcParams['figure.figsize'] = (10,5)
plt.bar(critters, counts)
plt.title('Number of samples per class in the training set\n')
plt.ylabel('Count\n')
plt.xlabel('\nClass')
plt.show()
```



```
[ ]: # Validation data
unique, counts = np.unique(Yval, return_counts=True)
pylab.rcParams['figure.figsize'] = (10,5)
plt.bar(critters, counts)
plt.title('Number of samples per class in the validation set\n')
plt.ylabel('Count\n')
plt.xlabel('\nClass')
plt.show()
```



```
[ ]: # Testing data
unique, counts = np.unique(Ytest, return_counts=True)
pylab.rcParams['figure.figsize'] = (10,5)
plt.bar(critters, counts)
plt.title('Number of samples per class in the testing set\n')
plt.ylabel('Count\n')
plt.xlabel('\nClass')
plt.show()
```



### Model functions

```
[ ]: def build_model(dropout, l2_val, activation=activation):

    if type(activation) != str:
        activ = 'LeakyReLU'
    else:
        activ = activation

    model = Sequential(name='Multi_Layer_Perceptron_{}_{}_DO_{}_L2'.format(activ,
↳ dropout, l2_val))
    model.add(Input(shape=(INPUT_DIM,),
                      name='Input'))
    model.add(Dense(32, activation=activation,
                    kernel_initializer='glorot_normal',
                    bias_initializer='zeros',
                    kernel_regularizer=L2(l2_val),
                    name='Dense1_{}'.format(activ)))
    model.add(BatchNormalization(name='BatchNormalization1'))
    model.add(Dense(32, activation=activation,
                    kernel_initializer='glorot_normal',
                    bias_initializer='zeros',
                    kernel_regularizer=L2(l2_val),
                    name='Dense2_{}'.format(activ)))
    model.add(Dropout(dropout, name='Dropout_{}'.format(dropout)))
    model.add(Dense(32, activation=activation,
```

```

        kernel_initializer='glorot_normal',
        bias_initializer='zeros',
        kernel_regularizer=L2(l2_val),
        name='Dense3_{}'.format(activ)))
model.add(Dense(32, activation=activation,
        kernel_initializer='glorot_normal',
        bias_initializer='zeros',
        kernel_regularizer=L2(l2_val),
        name='Dense4_{}'.format(activ)))
model.add(BatchNormalization(name='BatchNormalization2'))
model.add(Dense(16, activation=activation,
        kernel_initializer='glorot_normal',
        bias_initializer='zeros',
        kernel_regularizer=L2(l2_val),
        name='Dense5_{}'.format(activ)))
model.add(Dense(NUM_CLASSES, activation='softmax',
        name='Output'))

return model

```

```

[ ]: def compile_model(model, loss=loss, optimizer=optimizer, metrics=metrics):
    model.compile(loss=loss, optimizer=optimizer, metrics=metrics)

```

```

[ ]: def fit_model(model):
    start_time = time.time()
    history = model.fit(X_train, y_train,
                        epochs=EPOCHS,
                        batch_size=BATCH_SIZE,
                        validation_split=VALIDATION_SPLIT,
                        verbose=VERBOSE)

    time_taken = time.time() - start_time
    print(f'Total train time for {EPOCHS} epochs = %.3f' % time_taken,
          ↪ 'seconds\n\n')

    return history

```

```

[ ]: def evaluate_model(model):
    score = model.evaluate(X_test, y_test,
                           batch_size=BATCH_SIZE,
                           verbose=VERBOSE)

    return score

```

```

[ ]: def predict_model(model):
    y_pred = model.predict(X_test, batch_size=BATCH_SIZE)

    return y_pred

```

```
[ ]: def plot_accuracy(history, score, metrics=metrics):
    plt.plot(history.history[metrics[0]])
    plt.plot(history.history['val_'+metrics[0]])

    plt.title('Training and validation accuracy')
    plt.ylabel('Accuracy')
    plt.xlabel('Epoch')
    plt.yticks(ticks=[0.5, 0.6, 0.7, 0.8, 0.9, 1.0])
    plt.legend(['Training accuracy', 'Validation accuracy'], loc='best')
    plt.show()

    print(f'Test accuracy: {score[1]:.4}\n\n')

[ ]: def plot_loss(history, score):
    plt.plot(history.history['loss'])
    plt.plot(history.history['val_loss'])

    plt.title('Training and validation loss')
    plt.ylabel('Loss')
    plt.xlabel('Epoch')
    plt.yticks(ticks=[0.0, 0.2, 0.4, 0.6, 0.8, 1.0, 1.2])
    plt.legend(['Training loss', 'Validation loss'], loc='best')
    plt.show()

    print(f'Test loss: {score[0]:.4}\n\n')

[ ]: def print_classification_report(y_pred):
    print(cr(y_test, y_pred.argmax(axis=1), target_names=classes))

[ ]: def plot_confusion_matrix(y_pred):
    # source: https://stackoverflow.com/questions/20927368/how-to-normalize-a-confusion-matrix
    cmatrix = cm(y_test, y_pred.argmax(axis=1))
    cmatrix_norm = cmatrix.astype('float') / cmatrix.sum(axis=1)[:, np.newaxis]
    fig, ax = plt.subplots(figsize=(8,4))
    sns.heatmap(cmatrix_norm, annot=True, fmt="0.3f", xticklabels=classes,
    yticklabels=classes)
    plt.ylabel('Actual')
    plt.xlabel('Predicted')
    plt.title('Normalized confusion matrix')
    plt.show(block=False)

[ ]: def plot_precision_recall_curve(y_pred):
    n_classes = len(classes)
    y_test_ohe = to_categorical(y_test, num_classes=NUM_CLASSES)
```

```

# source: https://stackoverflow.com/questions/56090541/
→how-to-plot-precision-and-recall-of-multiclass-classifier
# precision recall curve
precision = dict()
recall = dict()
for i in range(n_classes):
    precision[i], recall[i], _ = precision_recall_curve(y_test_ohe[:, i],
                                                         y_pred[:, i])
    plt.plot(recall[i], precision[i], lw=1, label='{}'.format(classes[i]))

plt.xlabel("Recall")
plt.ylabel("Precision")
plt.legend(loc="best")
plt.title("Precision-Recall curve")
plt.show()

```

```

[ ]: def plot_roc_curve(y_pred):
    # source: https://stackoverflow.com/questions/64924911/
    →plotting-multiclass-roc-curve
    # Compute ROC curve and ROC area for each class
    n_classes = len(classes)
    y_test_ohe = to_categorical(y_test, num_classes=NUM_CLASSES)
    fpr = dict()
    tpr = dict()
    roc_auc = dict()
    for i in range(n_classes):
        fpr[i], tpr[i], _ = roc_curve(y_test_ohe[:, i], y_pred[:, i])
        roc_auc[i] = auc(fpr[i], tpr[i])

    # Compute micro-average ROC curve and ROC area
    fpr["micro"], tpr["micro"], _ = roc_curve(y_test_ohe.ravel(), y_pred.
    →ravel())
    roc_auc["micro"] = auc(fpr["micro"], tpr["micro"])

    lw=1

    # First aggregate all false positive rates
    all_fpr = np.unique(np.concatenate([fpr[i] for i in range(n_classes)]))

    # Then interpolate all ROC curves at this points
    mean_tpr = np.zeros_like(all_fpr)
    for i in range(n_classes):
        mean_tpr += np.interp(all_fpr, fpr[i], tpr[i])

    # Finally average it and compute AUC
    mean_tpr /= n_classes

```



```

fpr["macro"] = all_fpr
tpr["macro"] = mean_tpr
roc_auc["macro"] = auc(fpr["macro"], tpr["macro"])

# Plot all ROC curves
plt.figure()
plt.plot(fpr["micro"], tpr["micro"],
         label='micro-average ROC curve (area = {0:0.2f})'
         ''.format(roc_auc["micro"]),
         color='deeppink', linestyle=':', linewidth=4)

plt.plot(fpr["macro"], tpr["macro"],
         label='macro-average ROC curve (area = {0:0.2f})'
         ''.format(roc_auc["macro"]),
         color='cornflowerblue', linestyle=':', linewidth=4)

colors = cycle(['darkgreen', 'darkorange', 'navy', 'hotpink', 'maroon', 'cyan'])
for i, color in zip(range(n_classes), colors):
    plt.plot(fpr[i], tpr[i], color=color, lw=lw,
             label='ROC curve of class {0} (area = {1:0.2f})'
             ''.format(classes[i], roc_auc[i]))

plt.plot([0, 1], [0, 1], 'k--', lw=lw)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Some extension of Receiver operating characteristic to
multi-class')
plt.legend(loc="lower right")
plt.show()

```

```

[ ]: def print_auc_scores(y_pred):
    # source:https://scikit-learn.org/stable/auto_examples/model_selection/
    plot_roc.html
    macro_roc_auc_ovo = roc_auc_score(y_test, y_pred, multi_class="ovo",
                                     average="macro")
    weighted_roc_auc_ovo = roc_auc_score(y_test, y_pred, multi_class="ovo",
                                     average="weighted")
    macro_roc_auc_ovr = roc_auc_score(y_test, y_pred, multi_class="ovr",
                                     average="macro")
    weighted_roc_auc_ovr = roc_auc_score(y_test, y_pred, multi_class="ovr",
                                     average="weighted")
    print("One-vs-One ROC AUC scores:\n{:.6f} (macro),\n{:.6f} "
          "(weighted by prevalence)"
          .format(macro_roc_auc_ovo, weighted_roc_auc_ovo))

```

```
print("One-vs-Rest ROC AUC scores:\n{:.6f} (macro),\n{:.6f} "
      "(weighted by prevalence)"
      .format(macro_roc_auc_ovr, weighted_roc_auc_ovr))
```

```
[ ]: def plot_model_png(model, dropout, l2_val, optimizer):
    if optimizer == SGD:
        plot_path = '../MLP_sgd_'+str(dropout)+'DO_'+str(l2_val)+'L2.png'
    elif type(optimizer) != str:
        plot_path = '../MLP_adam_'+str(dropout)+'DO_'+str(l2_val)+'L2.png'
    else:
        plot_path = '../MLP_'+optimizer+'_'+str(dropout)+'DO_'+str(l2_val)+'L2.
→png'
    plot_model(model, to_file=os.path.join(DATA_DIR, plot_path),
→show_shapes=True)
```

```
[ ]: def run_model(dropout=0, l2_val=0, activation=activation,
                    loss=loss, optimizer=optimizer, metrics=metrics):
    model = build_model(dropout, l2_val, activation)
    model.summary()
    plot_model_png(model, dropout, l2_val, optimizer)
    compile_model(model)
    history = fit_model(model)
    score = evaluate_model(model)
    y_pred = predict_model(model)
    plot_accuracy(history, score)
    plot_loss(history, score)
    print_classification_report(y_pred)
    print('\n\n')
    plot_confusion_matrix(y_pred)
    print('\n\n')
    plot_precision_recall_curve(y_pred)
    print('\n\n')
    plot_roc_curve(y_pred)
    print('\n\n')
    print_auc_scores(y_pred)
    print('\n\n')

    return model, history, score, y_pred
```

## 0.5 Run models

```
[ ]: model_base, history_base, score_base, y_pred_base = run_model()
```

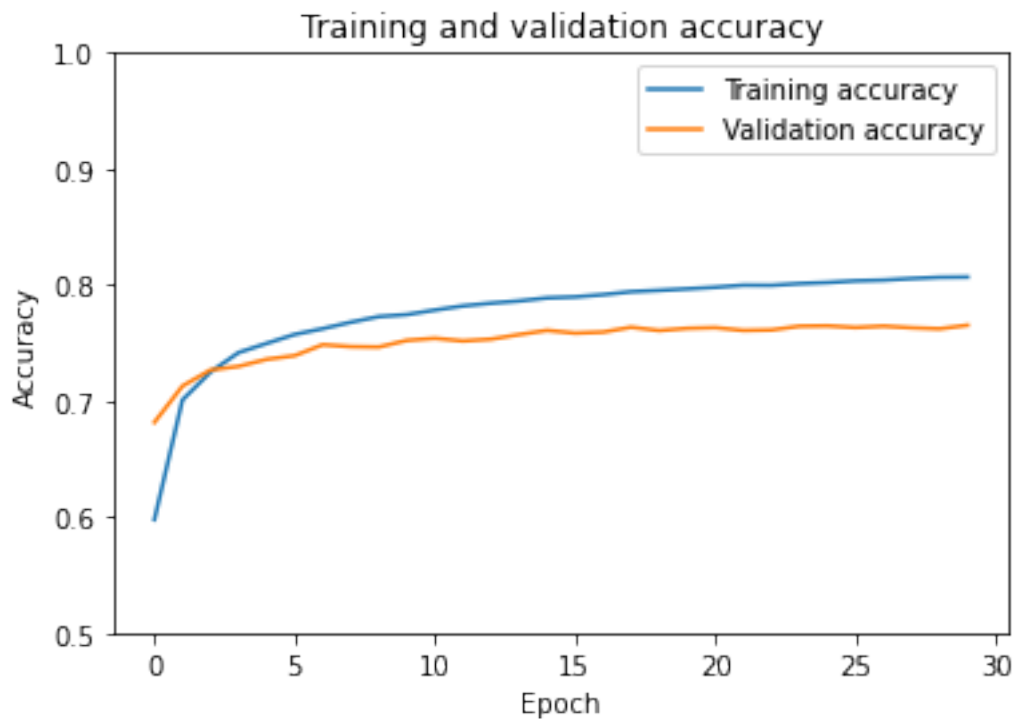
Model: "Multi\_Layer\_Perceptron\_LeakyReLU\_OD0\_OL2"

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

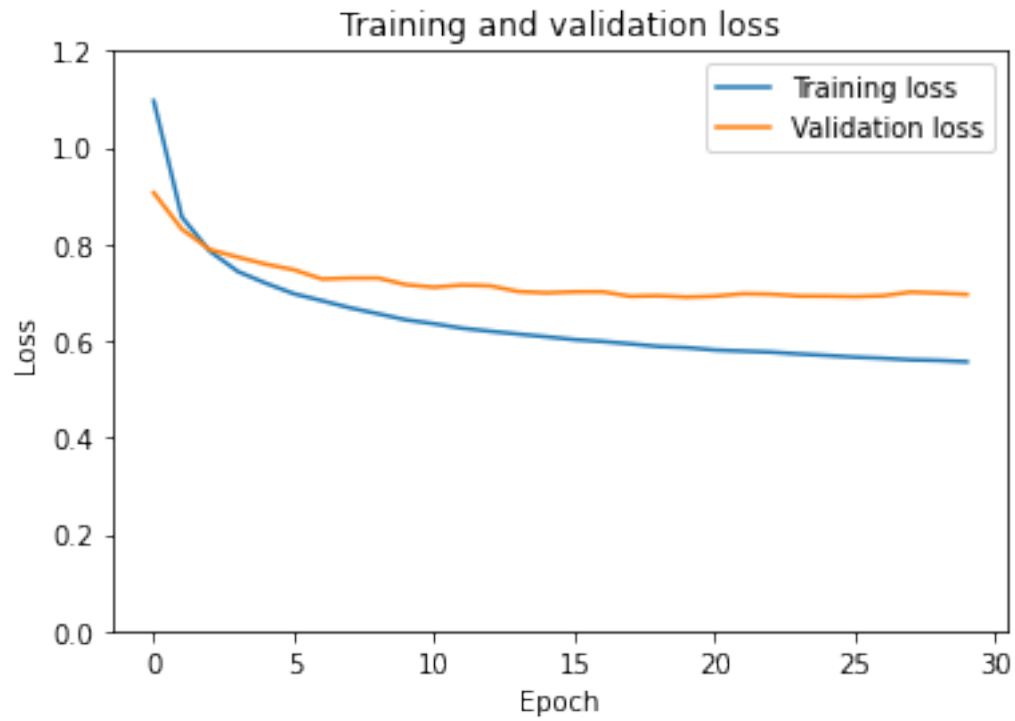
```

=====
Dense1_LeakyReLU (Dense)      (None, 32)      25120
-----
BatchNormalization1 (BatchNo (None, 32)      128
-----
Dense2_LeakyReLU (Dense)      (None, 32)      1056
-----
Dropout_0 (Dropout)           (None, 32)      0
-----
Dense3_LeakyReLU (Dense)      (None, 32)      1056
-----
Dense4_LeakyReLU (Dense)      (None, 32)      1056
-----
BatchNormalization2 (BatchNo (None, 32)      128
-----
Dense5_LeakyReLU (Dense)      (None, 16)      528
-----
Output (Dense)                (None, 6)       102
=====
Total params: 29,174
Trainable params: 29,046
Non-trainable params: 128
-----
Total train time for 30 epochs = 71.950 seconds

```

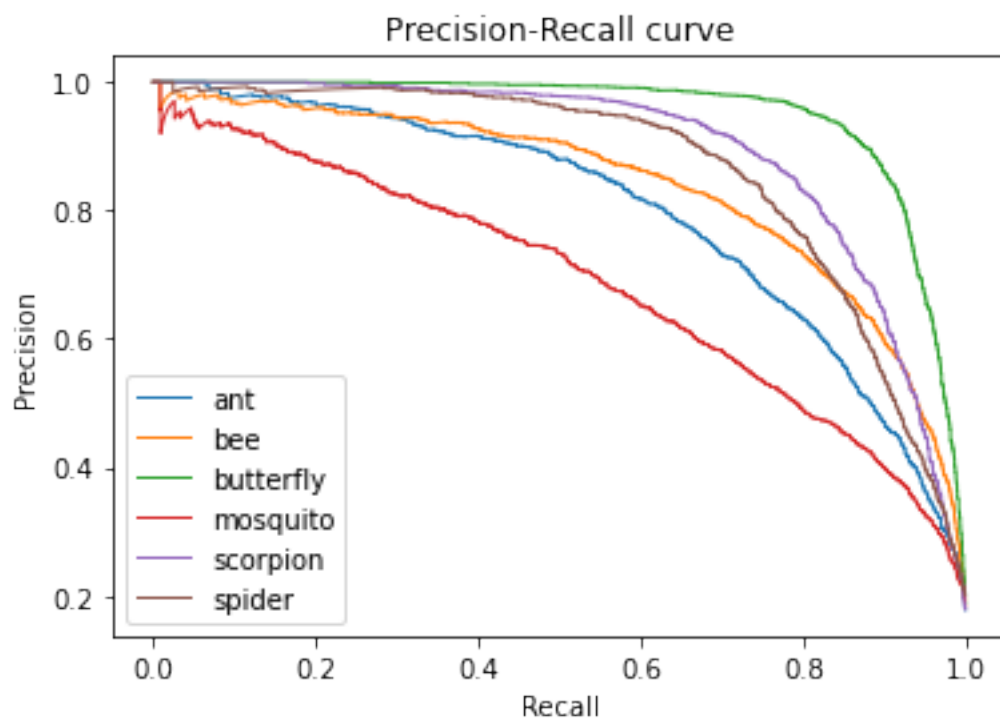
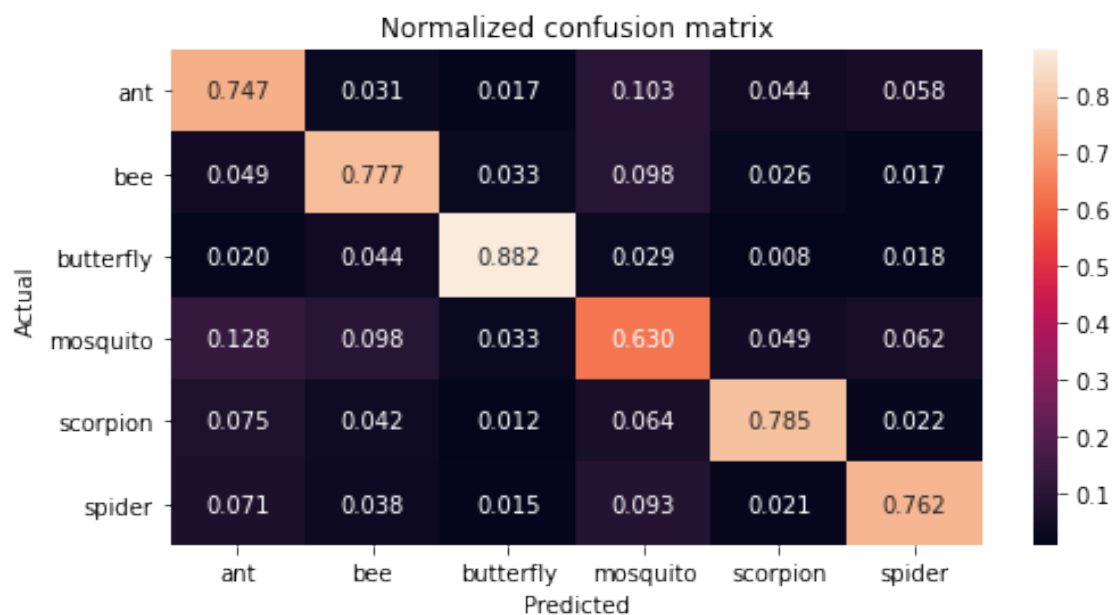


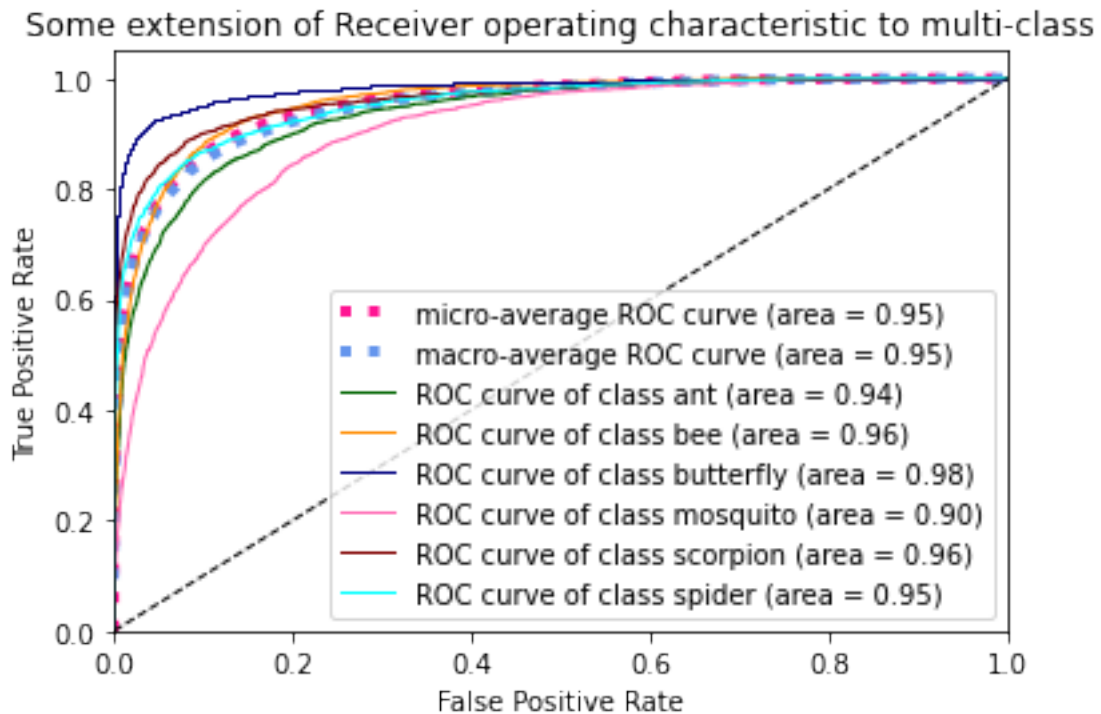
Test accuracy: 0.7641



Test loss: 0.6984

	precision	recall	f1-score	support
ant	0.68	0.75	0.71	2478
bee	0.75	0.78	0.76	2488
butterfly	0.89	0.88	0.89	2557
mosquito	0.62	0.63	0.63	2527
scorpion	0.84	0.79	0.81	2468
spider	0.81	0.76	0.79	2482
accuracy			0.76	15000
macro avg	0.77	0.76	0.76	15000
weighted avg	0.77	0.76	0.77	15000





One-vs-One ROC AUC scores:  
0.948369 (macro),  
0.948412 (weighted by prevalence)  
One-vs-Rest ROC AUC scores:  
0.948432 (macro),  
0.948461 (weighted by prevalence)

```
[ ]: model_10do, history_10do, score_10do, y_pred_10do = run_model(dropout=0.1)
```

Model: "Multi\_Layer\_Perceptron\_LeakyReLU\_0.1D0\_OL2"

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

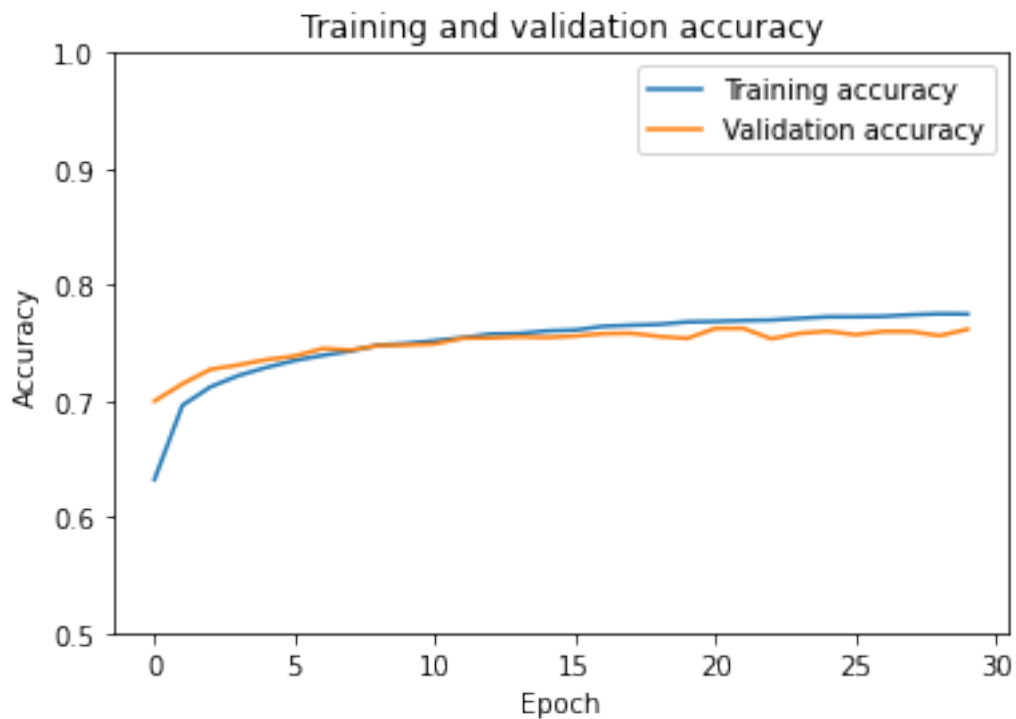
Dense1_LeakyReLU (Dense)	(None, 32)	25120
BatchNormalization1 (BatchNo	(None, 32)	128
Dense2_LeakyReLU (Dense)	(None, 32)	1056
Dropout_0.1 (Dropout)	(None, 32)	0
Dense3_LeakyReLU (Dense)	(None, 32)	1056
Dense4_LeakyReLU (Dense)	(None, 32)	1056
BatchNormalization2 (BatchNo	(None, 32)	128
Dense5_LeakyReLU (Dense)	(None, 16)	528
Output (Dense)	(None, 6)	102

Total params: 29,174

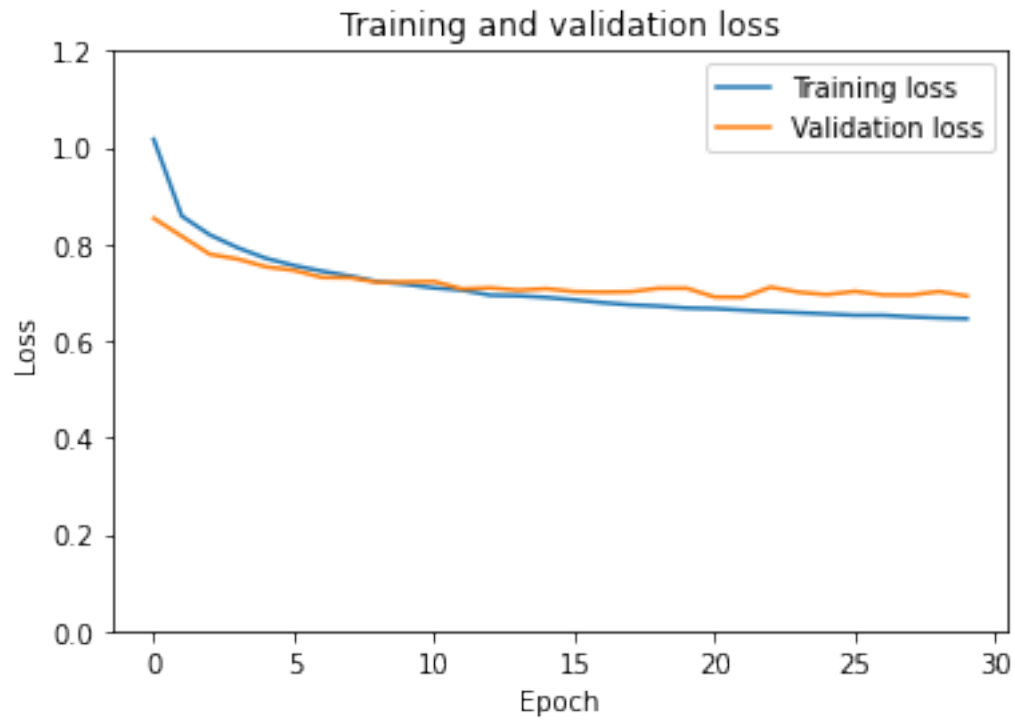
Trainable params: 29,046

Non-trainable params: 128

Total train time for 30 epochs = 70.748 seconds



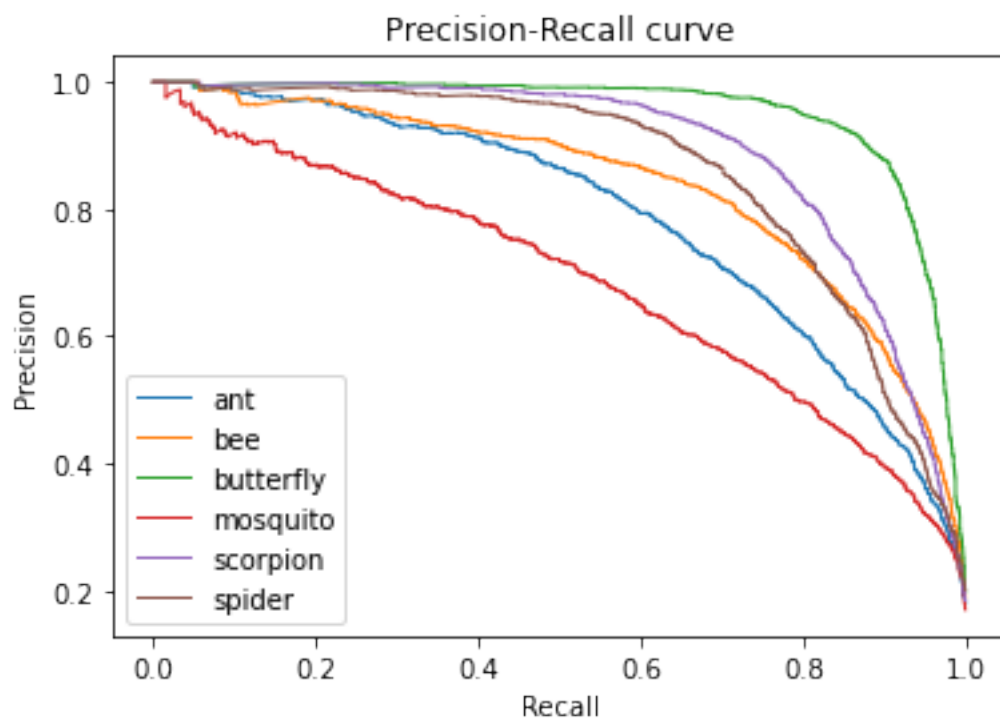
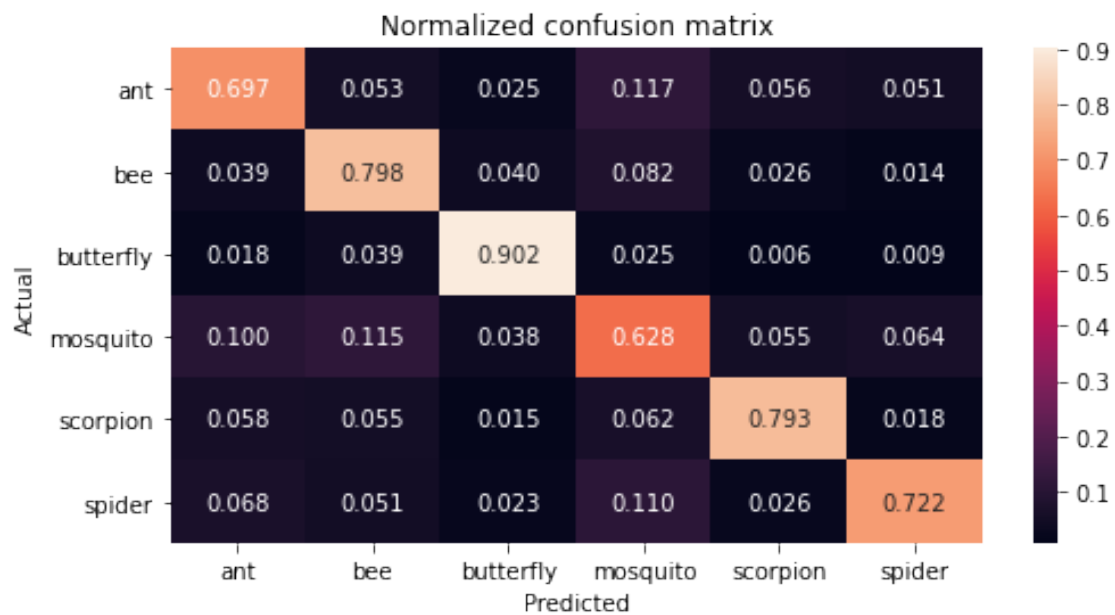
Test accuracy: 0.7571

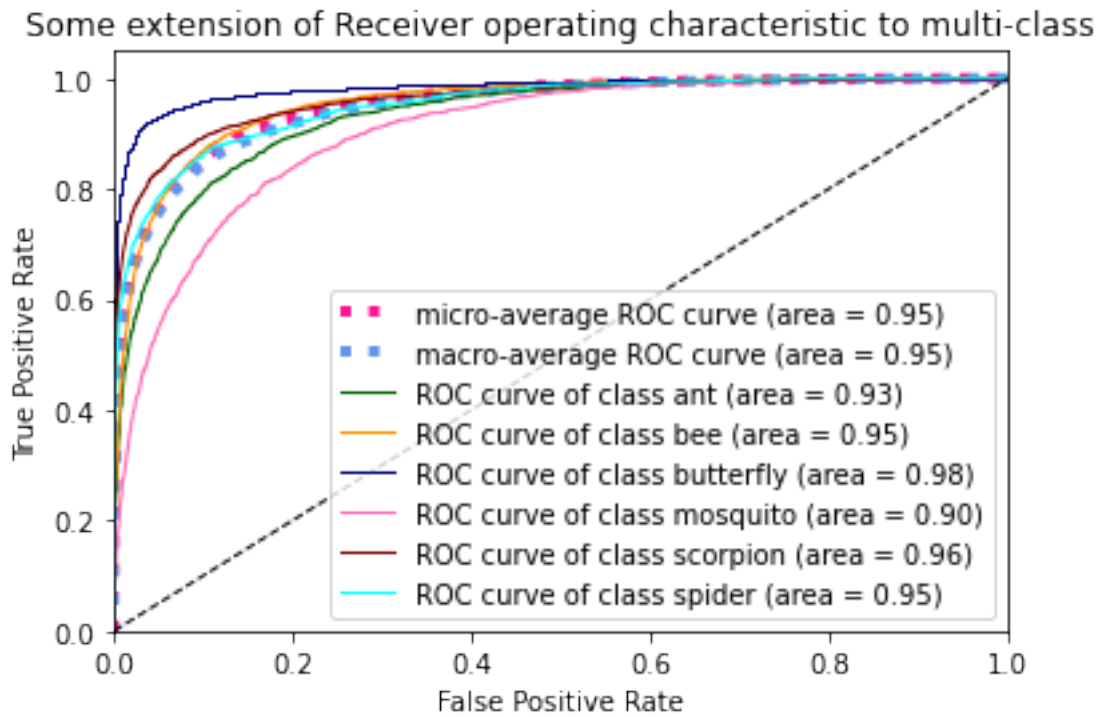


Test loss: 0.6967

	precision	recall	f1-score	support
ant	0.71	0.70	0.70	2478
bee	0.72	0.80	0.75	2488
butterfly	0.87	0.90	0.88	2557
mosquito	0.62	0.63	0.62	2527
scorpion	0.82	0.79	0.81	2468
spider	0.82	0.72	0.77	2482
accuracy			0.76	15000
macro avg	0.76	0.76	0.76	15000
weighted avg	0.76	0.76	0.76	15000







One-vs-One ROC AUC scores:  
0.946891 (macro),  
0.946948 (weighted by prevalence)  
One-vs-Rest ROC AUC scores:  
0.946973 (macro),  
0.947013 (weighted by prevalence)

```
[ ]: model_20do, history_20do, score_20do, y_pred_20do = run_model(dropout=0.2)
```

Model: "Multi\_Layer\_Perceptron\_LeakyReLU\_0.2D0\_0L2"

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

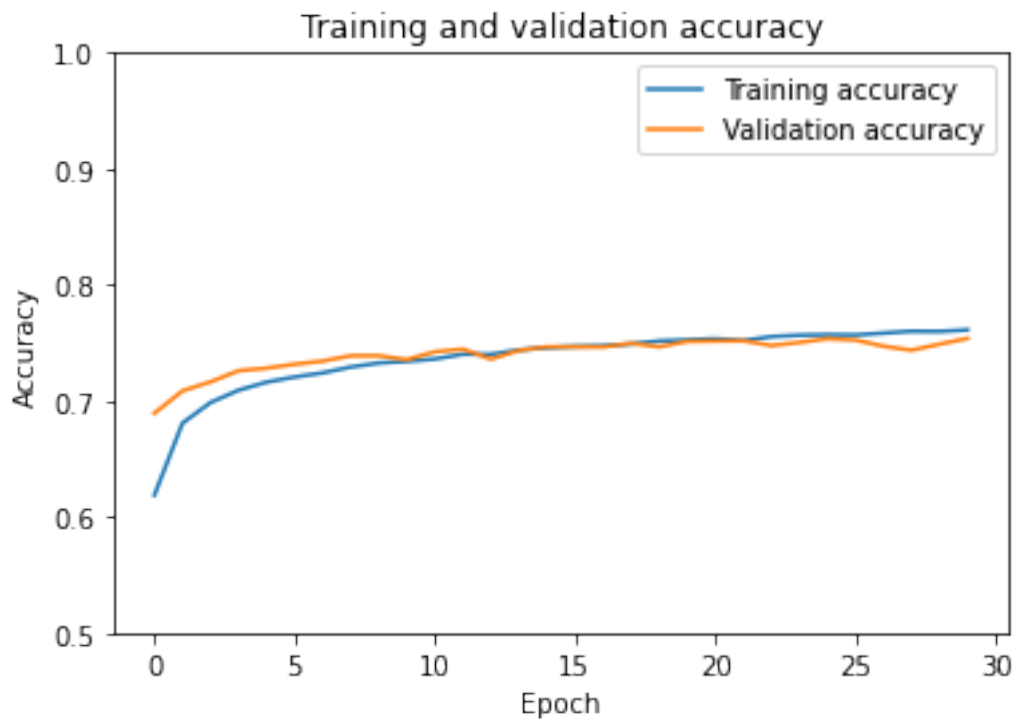
Dense1_LeakyReLU (Dense)	(None, 32)	25120
BatchNormalization1 (BatchNo	(None, 32)	128
Dense2_LeakyReLU (Dense)	(None, 32)	1056
Dropout_0.2 (Dropout)	(None, 32)	0
Dense3_LeakyReLU (Dense)	(None, 32)	1056
Dense4_LeakyReLU (Dense)	(None, 32)	1056
BatchNormalization2 (BatchNo	(None, 32)	128
Dense5_LeakyReLU (Dense)	(None, 16)	528
Output (Dense)	(None, 6)	102

Total params: 29,174

Trainable params: 29,046

Non-trainable params: 128

Total train time for 30 epochs = 71.239 seconds

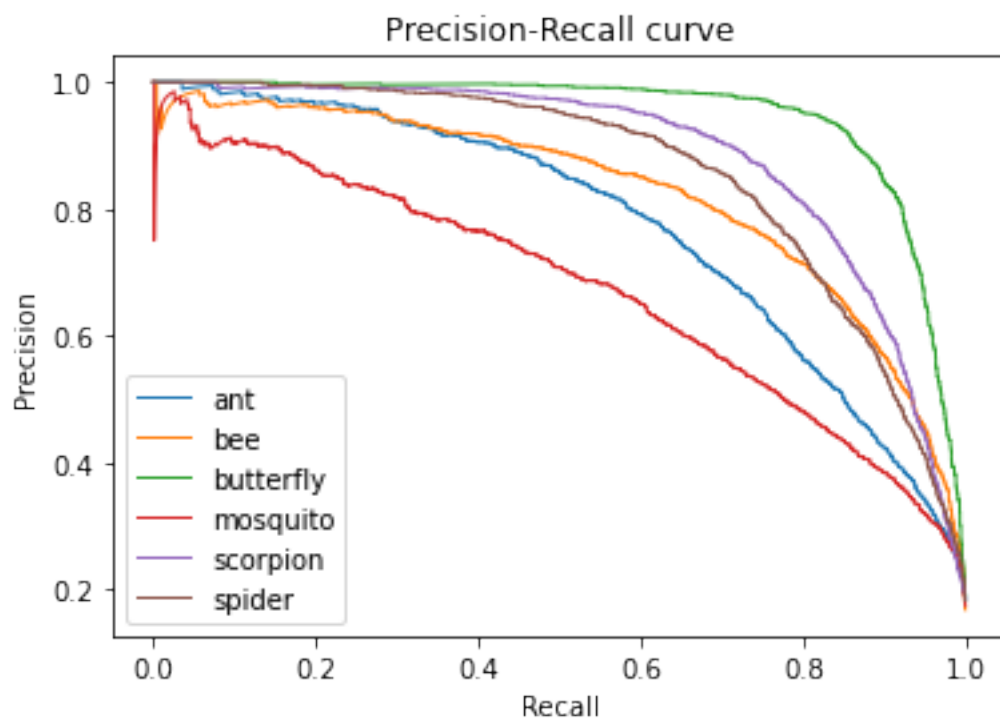
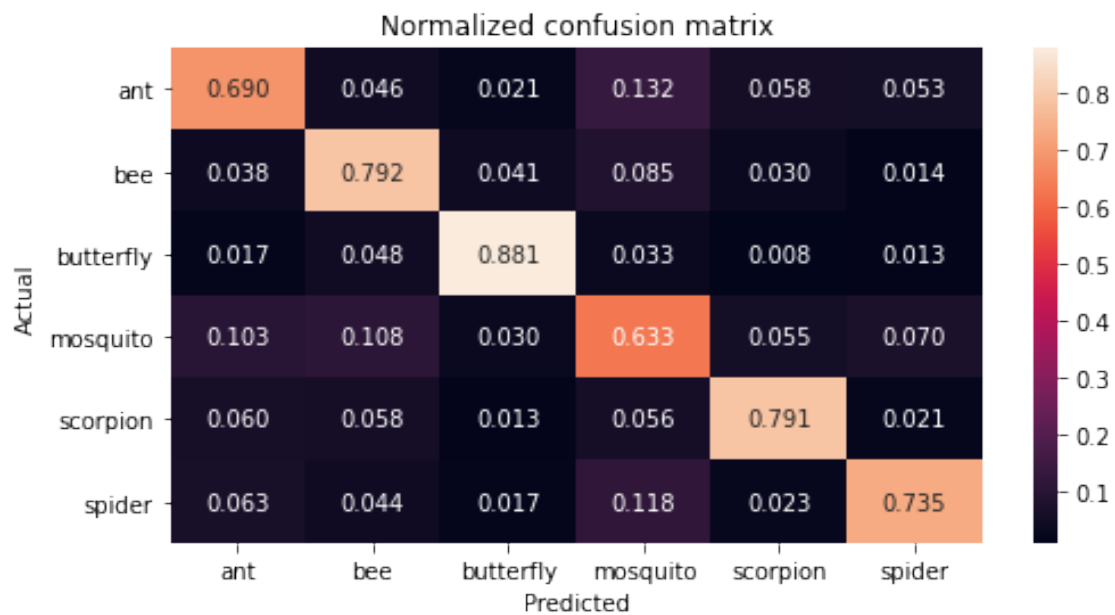


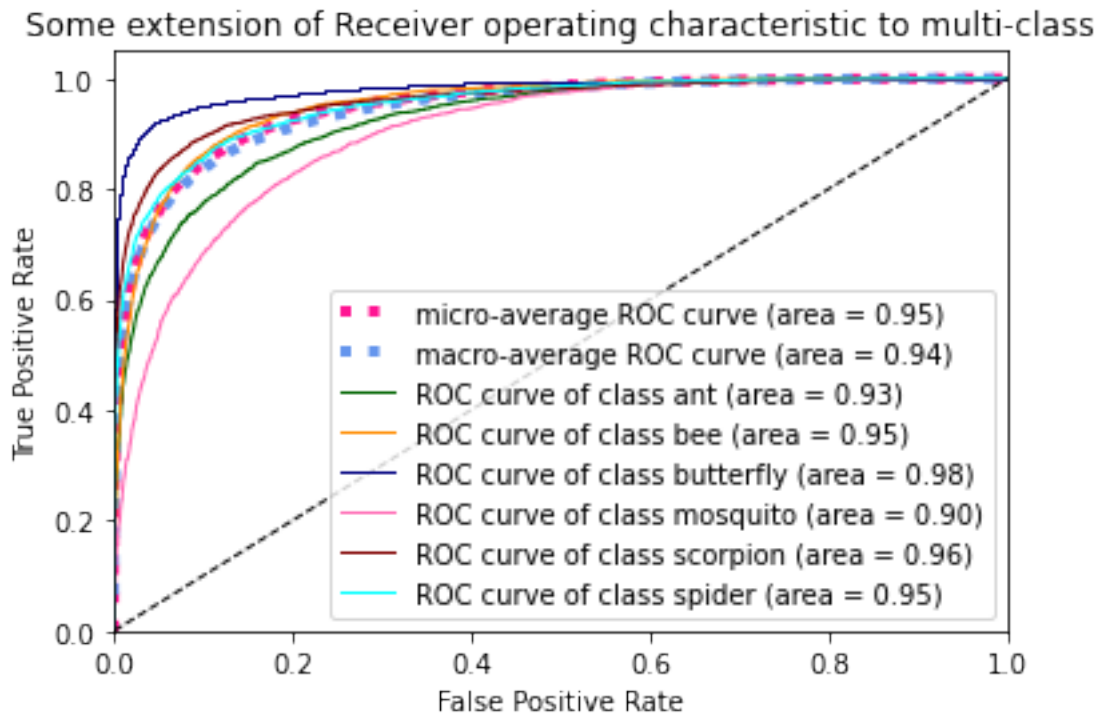
Test accuracy: 0.7538



Test loss: 0.7123

	precision	recall	f1-score	support
ant	0.71	0.69	0.70	2478
bee	0.72	0.79	0.75	2488
butterfly	0.88	0.88	0.88	2557
mosquito	0.60	0.63	0.62	2527
scorpion	0.82	0.79	0.80	2468
spider	0.81	0.74	0.77	2482
accuracy			0.75	15000
macro avg	0.76	0.75	0.75	15000
weighted avg	0.76	0.75	0.75	15000





One-vs-One ROC AUC scores:  
0.944132 (macro),  
0.944187 (weighted by prevalence)  
One-vs-Rest ROC AUC scores:  
0.944211 (macro),  
0.944251 (weighted by prevalence)

```
[ ]: model_40do, history_40do, score_40do, y_pred_40do = run_model(dropout=0.4)
```

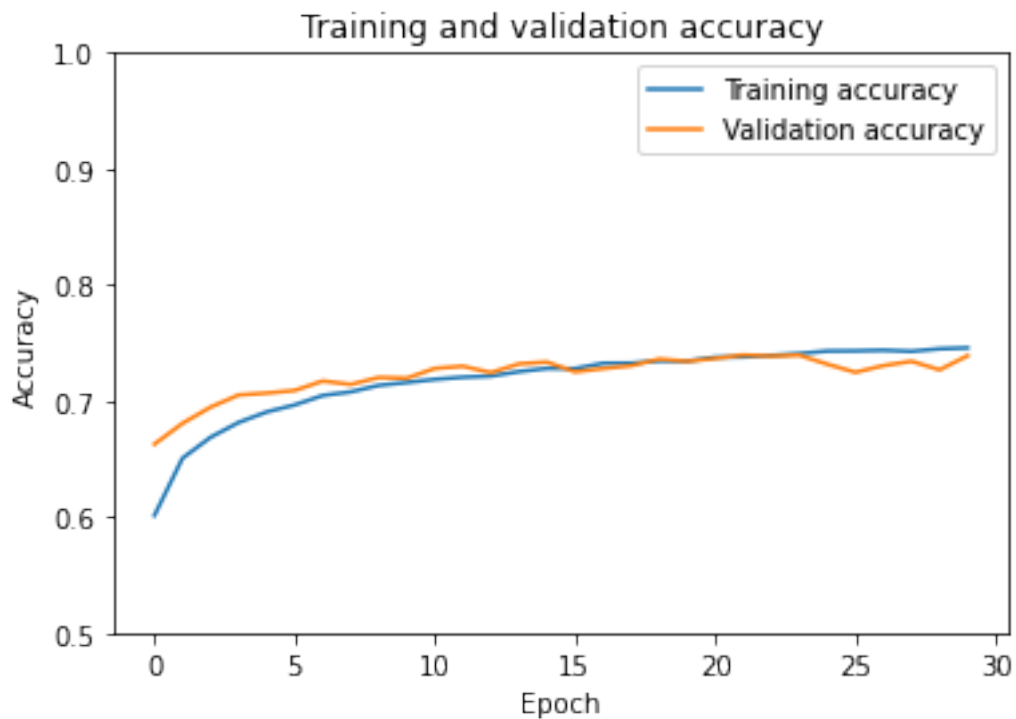
Model: "Multi\_Layer\_Perceptron\_LeakyReLU\_0.4D0\_0L2"

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

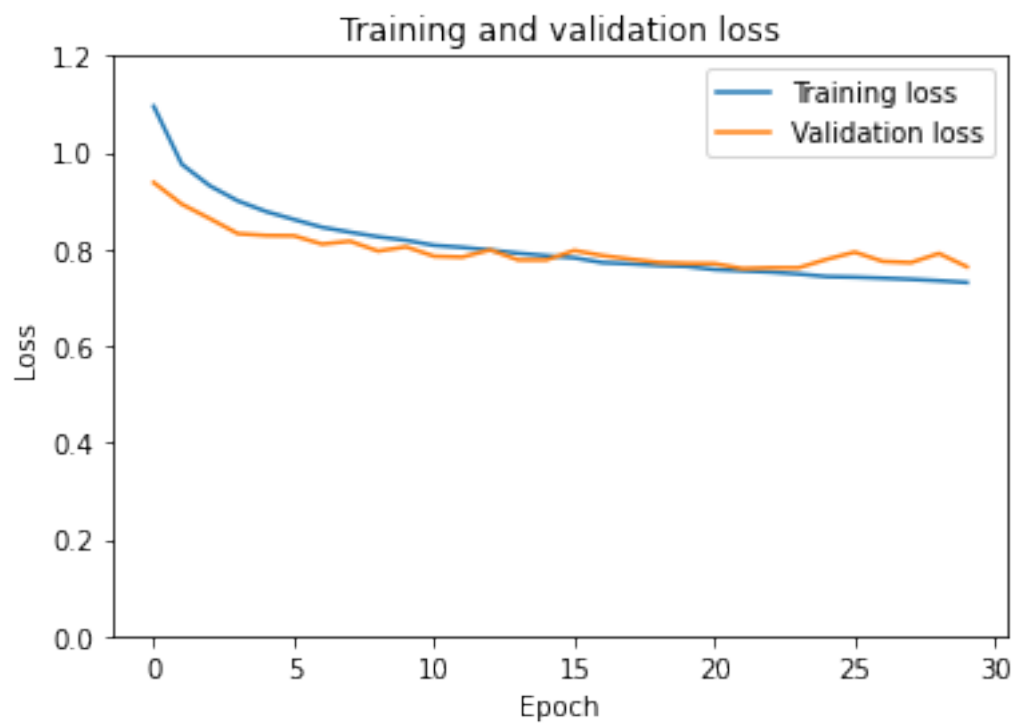
```

=====
Dense1_LeakyReLU (Dense)      (None, 32)      25120
-----
BatchNormalization1 (BatchNo (None, 32)      128
-----
Dense2_LeakyReLU (Dense)      (None, 32)      1056
-----
Dropout_0.4 (Dropout)         (None, 32)      0
-----
Dense3_LeakyReLU (Dense)      (None, 32)      1056
-----
Dense4_LeakyReLU (Dense)      (None, 32)      1056
-----
BatchNormalization2 (BatchNo (None, 32)      128
-----
Dense5_LeakyReLU (Dense)      (None, 16)      528
-----
Output (Dense)                (None, 6)       102
=====
Total params: 29,174
Trainable params: 29,046
Non-trainable params: 128
-----
Total train time for 30 epochs = 71.481 seconds

```



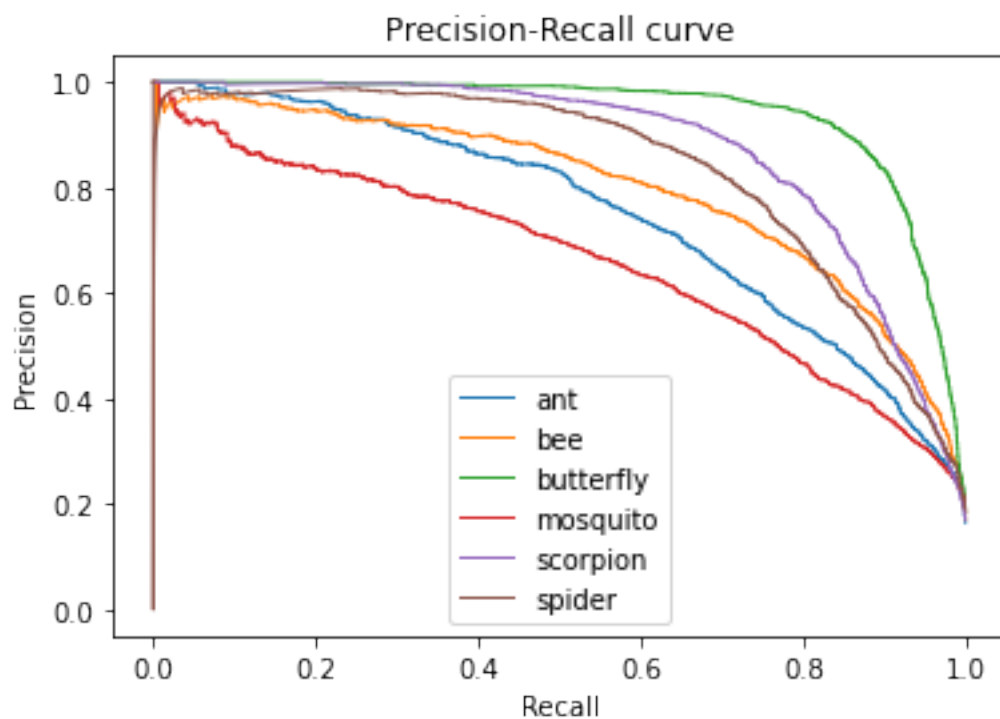
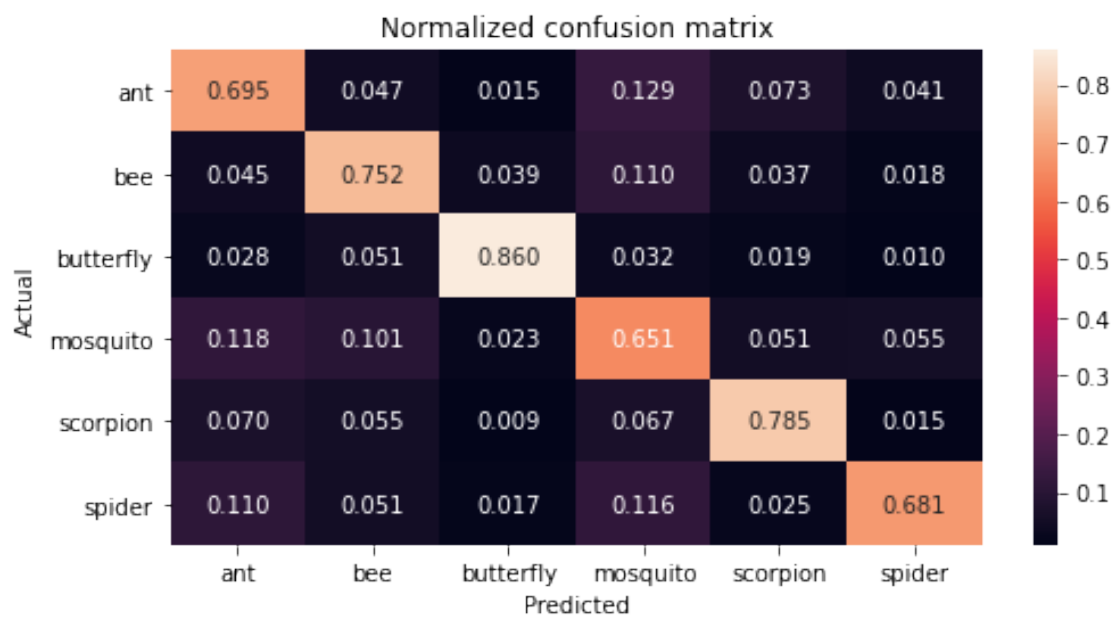
Test accuracy: 0.7375

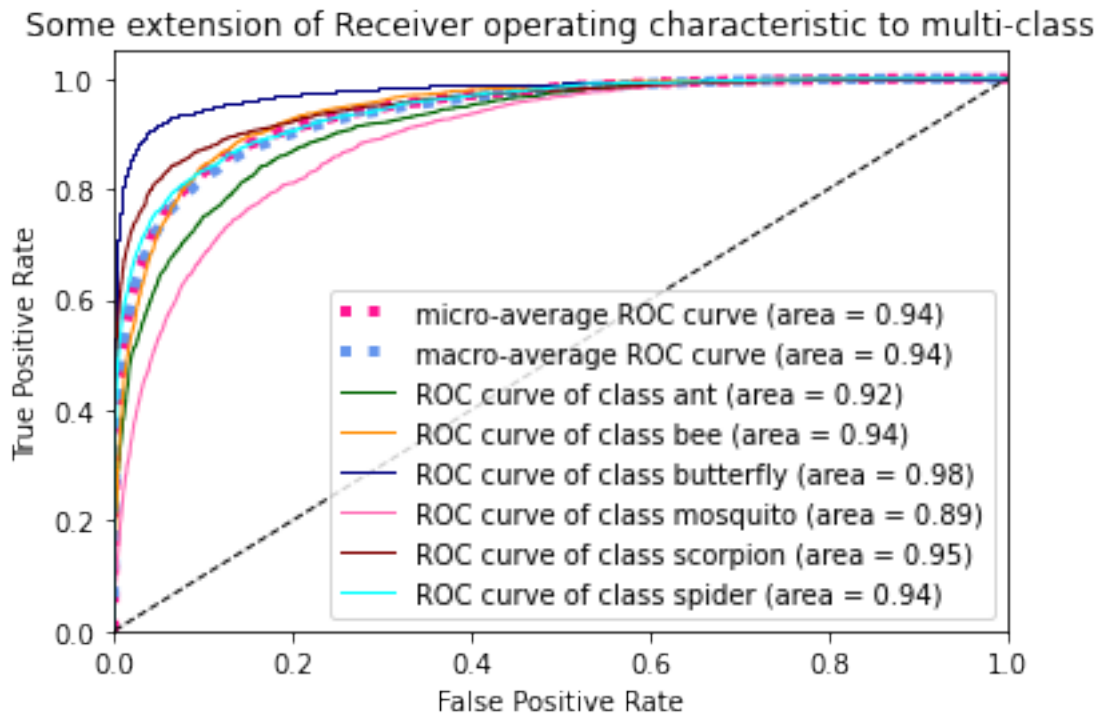


Test loss: 0.7637

	precision	recall	f1-score	support
ant	0.65	0.69	0.67	2478
bee	0.71	0.75	0.73	2488
butterfly	0.90	0.86	0.88	2557
mosquito	0.59	0.65	0.62	2527
scorpion	0.79	0.78	0.79	2468
spider	0.83	0.68	0.75	2482
accuracy			0.74	15000
macro avg	0.74	0.74	0.74	15000
weighted avg	0.74	0.74	0.74	15000







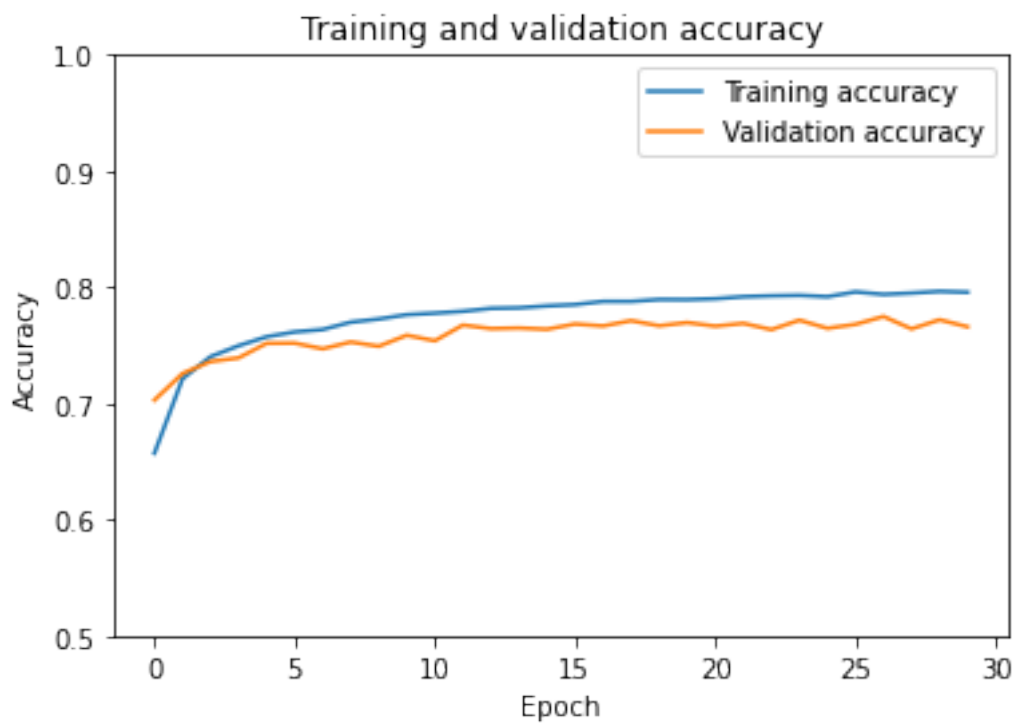
One-vs-One ROC AUC scores:  
 0.938007 (macro),  
 0.938062 (weighted by prevalence)  
 One-vs-Rest ROC AUC scores:  
 0.938068 (macro),  
 0.938130 (weighted by prevalence)

```
[ ]: model_0005L2, history_0005L2, score_0005L2, y_pred_0005L2 = run_model(l2_val=0.
    ↪0005)
```

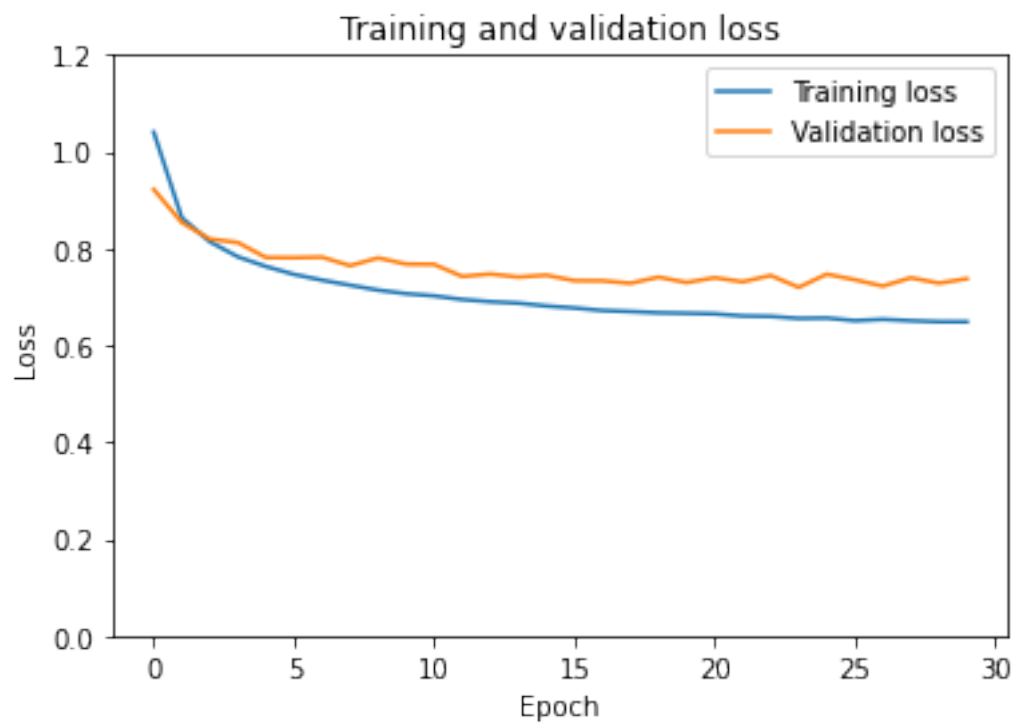
Model: "Multi\_Layer\_Perceptron\_LeakyReLU\_ODD\_0.0005L2"

---

Layer (type)	Output Shape	Param #
Dense1_LeakyReLU (Dense)	(None, 32)	25120
BatchNormalization1 (BatchNo	(None, 32)	128
Dense2_LeakyReLU (Dense)	(None, 32)	1056
Dropout_0 (Dropout)	(None, 32)	0
Dense3_LeakyReLU (Dense)	(None, 32)	1056
Dense4_LeakyReLU (Dense)	(None, 32)	1056
BatchNormalization2 (BatchNo	(None, 32)	128
Dense5_LeakyReLU (Dense)	(None, 16)	528
Output (Dense)	(None, 6)	102
Total params: 29,174		
Trainable params: 29,046		
Non-trainable params: 128		
Total train time for 30 epochs = 75.468 seconds		

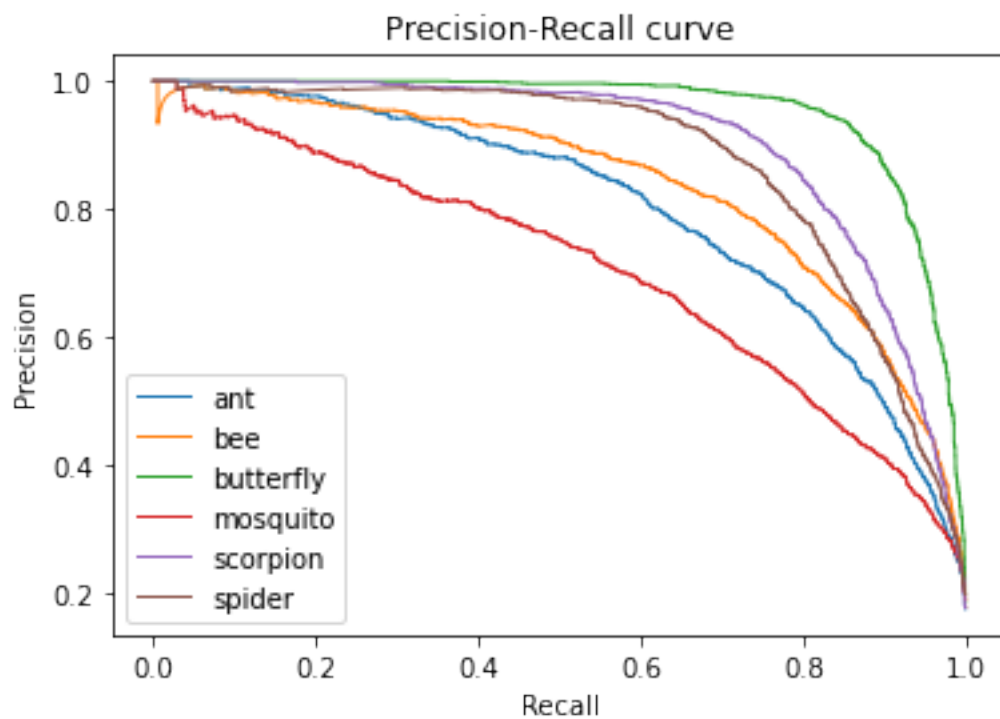
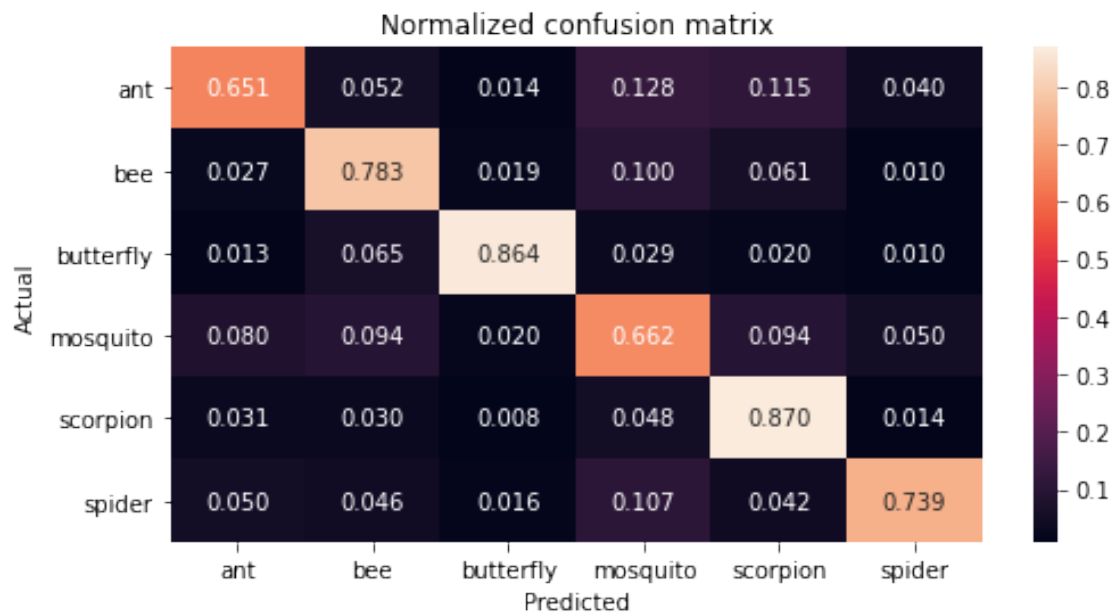


Test accuracy: 0.7613

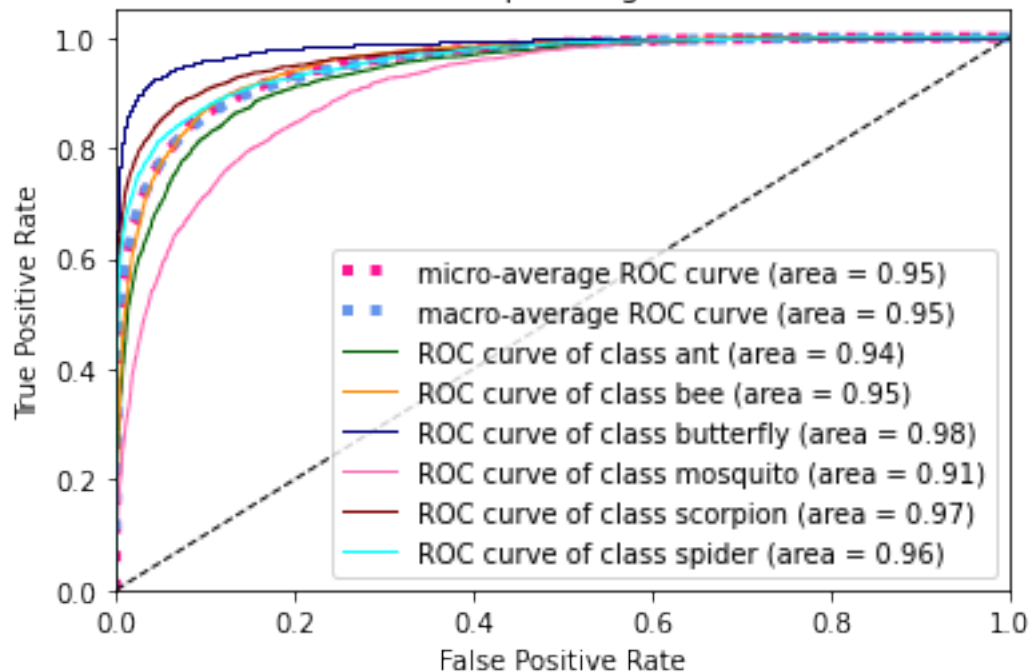


Test loss: 0.744

	precision	recall	f1-score	support
ant	0.76	0.65	0.70	2478
bee	0.73	0.78	0.76	2488
butterfly	0.92	0.86	0.89	2557
mosquito	0.62	0.66	0.64	2527
scorpion	0.72	0.87	0.79	2468
spider	0.86	0.74	0.79	2482
accuracy			0.76	15000
macro avg	0.77	0.76	0.76	15000
weighted avg	0.77	0.76	0.76	15000



Some extension of Receiver operating characteristic to multi-class



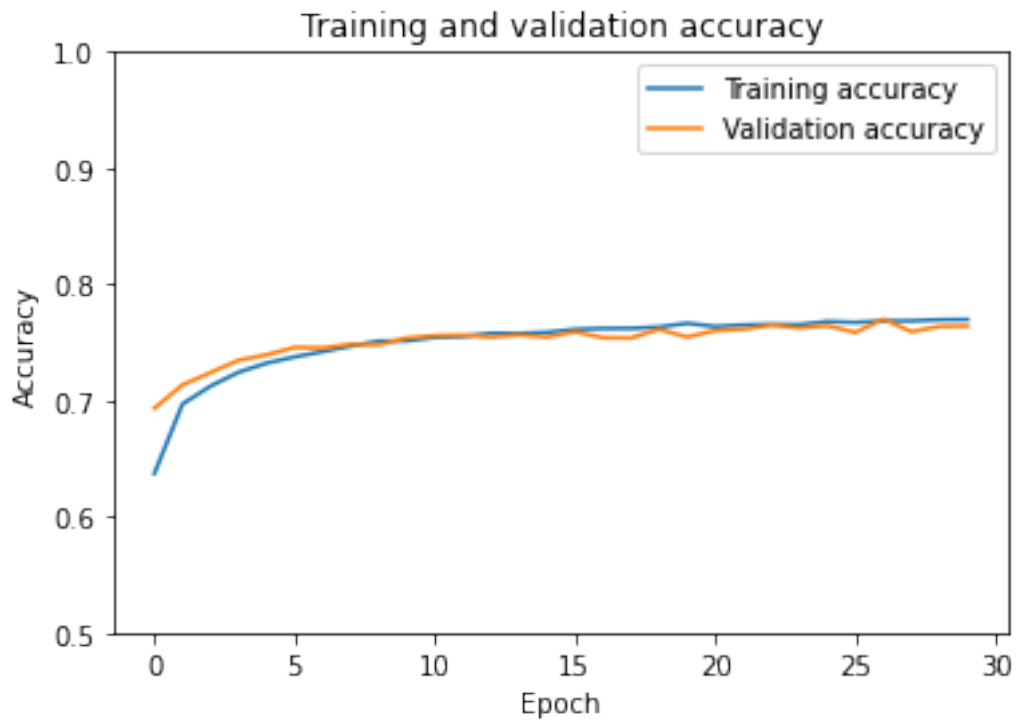
One-vs-One ROC AUC scores:  
 0.951254 (macro),  
 0.951290 (weighted by prevalence)  
 One-vs-Rest ROC AUC scores:  
 0.951299 (macro),  
 0.951332 (weighted by prevalence)

```
[ ]: model_0005L2_10do, history_0005L2_10do, score_0005L2_10do, y_pred_0005L2_10do = ↪run_model(l2_val=0.0005, dropout=0.1)
```

Model: "Multi\_Layer\_Perceptron\_LeakyReLU\_0.1D0\_0.0005L2"

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

Dense1_LeakyReLU (Dense)	(None, 32)	25120
-----		
BatchNormalization1 (BatchNo	(None, 32)	128
-----		
Dense2_LeakyReLU (Dense)	(None, 32)	1056
-----		
Dropout_0.1 (Dropout)	(None, 32)	0
-----		
Dense3_LeakyReLU (Dense)	(None, 32)	1056
-----		
Dense4_LeakyReLU (Dense)	(None, 32)	1056
-----		
BatchNormalization2 (BatchNo	(None, 32)	128
-----		
Dense5_LeakyReLU (Dense)	(None, 16)	528
-----		
Output (Dense)	(None, 6)	102
=====		
Total params: 29,174		
Trainable params: 29,046		
Non-trainable params: 128		
-----		
Total train time for 30 epochs = 75.215 seconds		



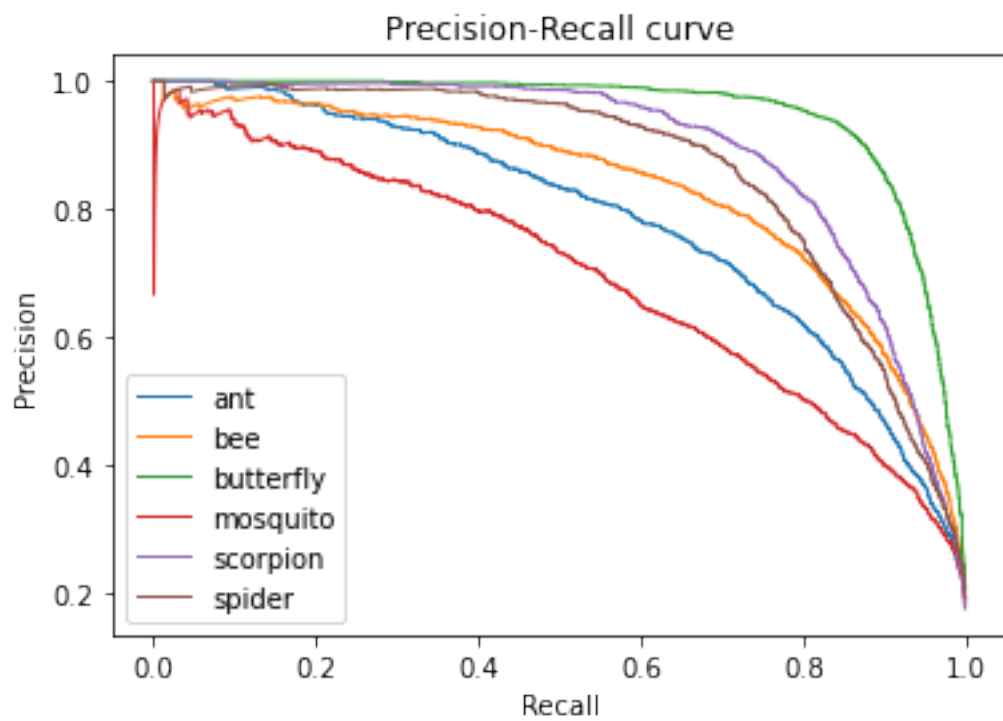
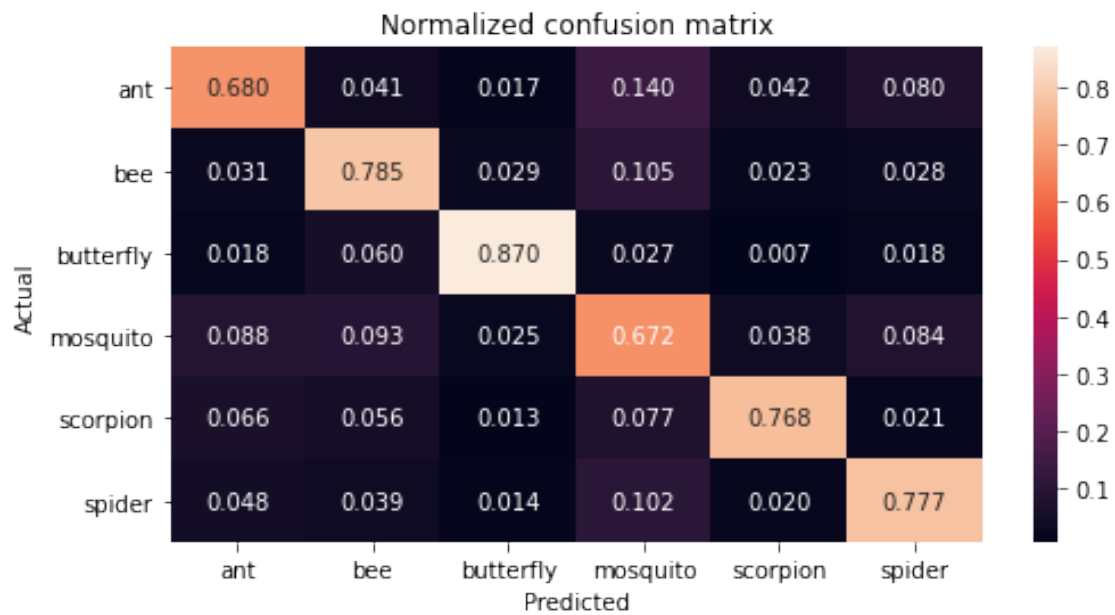


Test accuracy: 0.7588

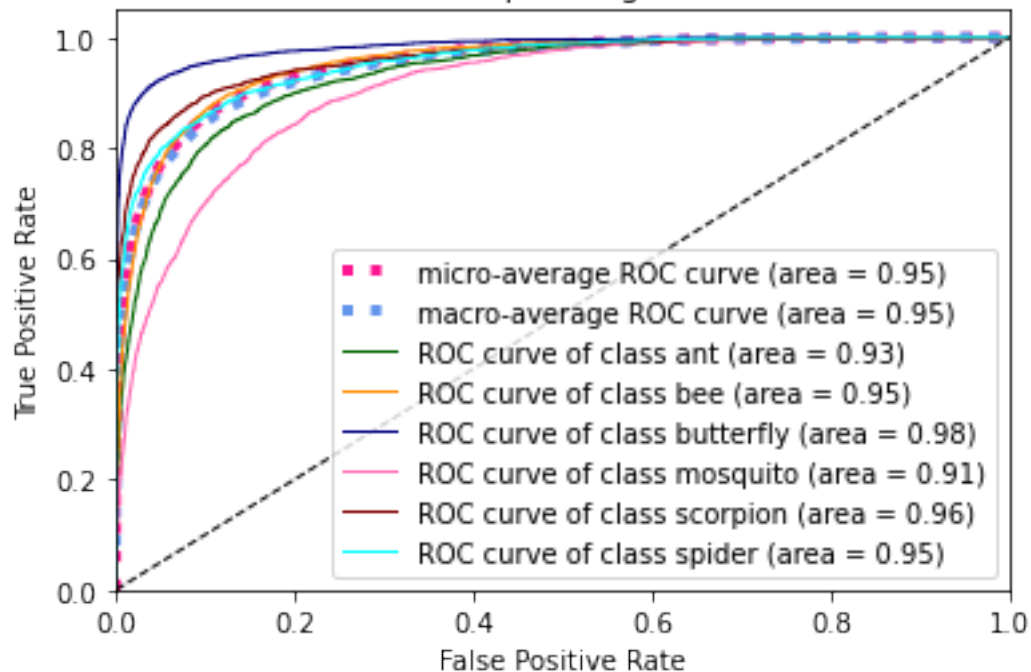


Test loss: 0.7538

	precision	recall	f1-score	support
ant	0.73	0.68	0.70	2478
bee	0.73	0.78	0.76	2488
butterfly	0.90	0.87	0.89	2557
mosquito	0.60	0.67	0.64	2527
scorpion	0.85	0.77	0.81	2468
spider	0.77	0.78	0.77	2482
accuracy			0.76	15000
macro avg	0.76	0.76	0.76	15000
weighted avg	0.76	0.76	0.76	15000



Some extension of Receiver operating characteristic to multi-class



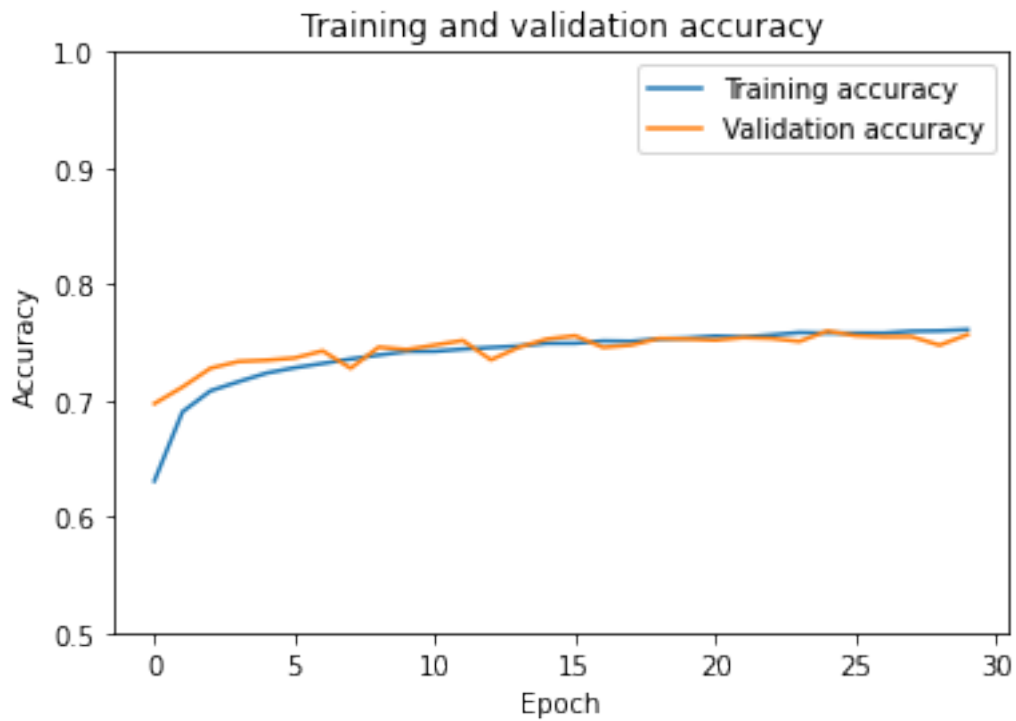
One-vs-One ROC AUC scores:  
 0.947766 (macro),  
 0.947825 (weighted by prevalence)  
 One-vs-Rest ROC AUC scores:  
 0.947850 (macro),  
 0.947892 (weighted by prevalence)

```
[ ]: model_0005L2_20do, history_0005L2_20do, score_0005L2_20do, y_pred_0005L2_20do = ↪ run_model(l2_val=0.0005, dropout=0.2)
```

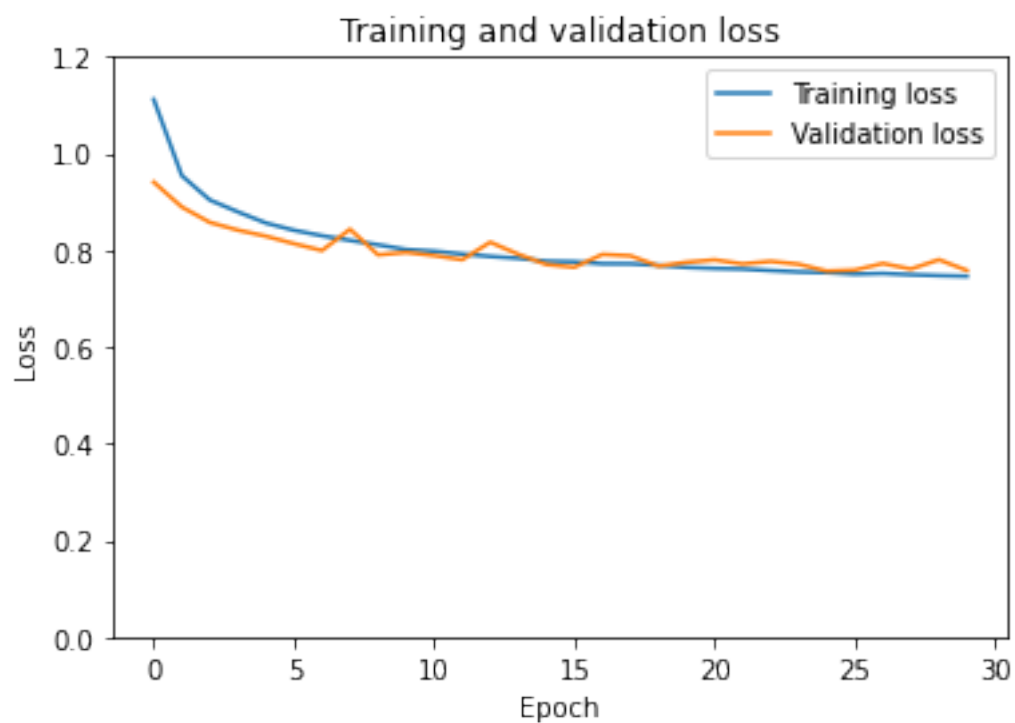
Model: "Multi\_Layer\_Perceptron\_LeakyReLU\_0.2D0\_0.0005L2"

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

Dense1_LeakyReLU (Dense)	(None, 32)	25120
-----		
BatchNormalization1 (BatchNo	(None, 32)	128
-----		
Dense2_LeakyReLU (Dense)	(None, 32)	1056
-----		
Dropout_0.2 (Dropout)	(None, 32)	0
-----		
Dense3_LeakyReLU (Dense)	(None, 32)	1056
-----		
Dense4_LeakyReLU (Dense)	(None, 32)	1056
-----		
BatchNormalization2 (BatchNo	(None, 32)	128
-----		
Dense5_LeakyReLU (Dense)	(None, 16)	528
-----		
Output (Dense)	(None, 6)	102
=====		
Total params: 29,174		
Trainable params: 29,046		
Non-trainable params: 128		
-----		
Total train time for 30 epochs = 75.258 seconds		

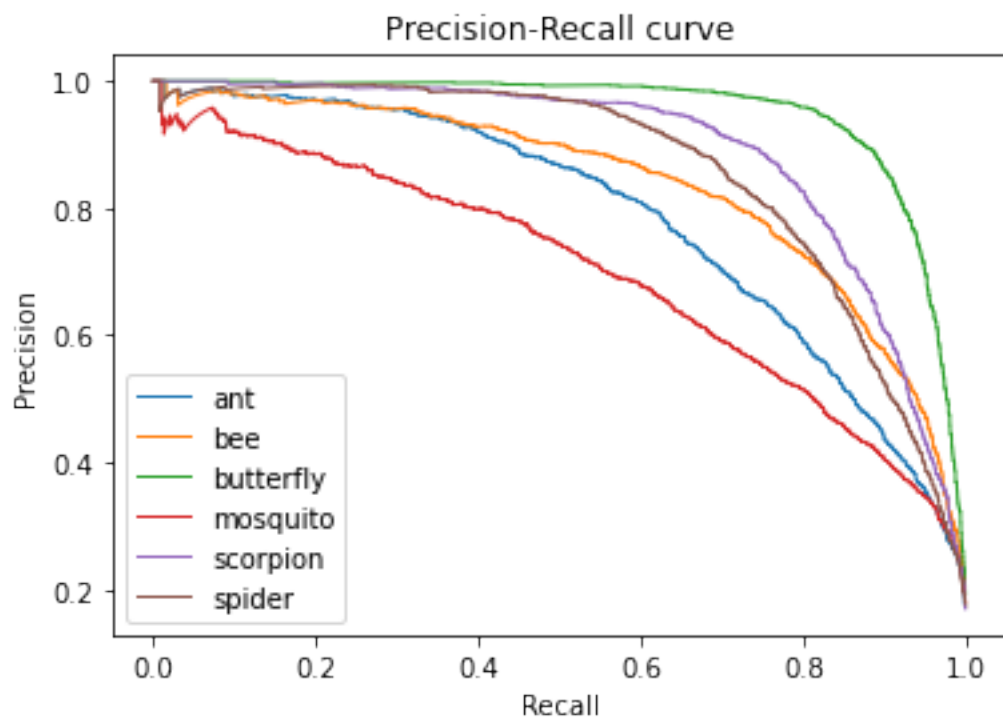
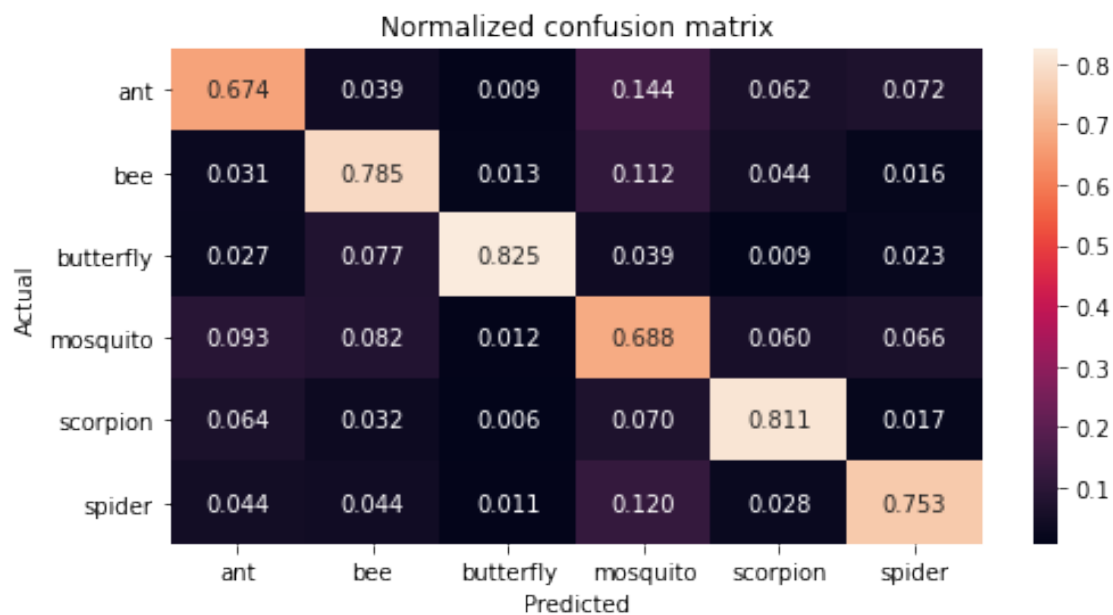


Test accuracy: 0.7559

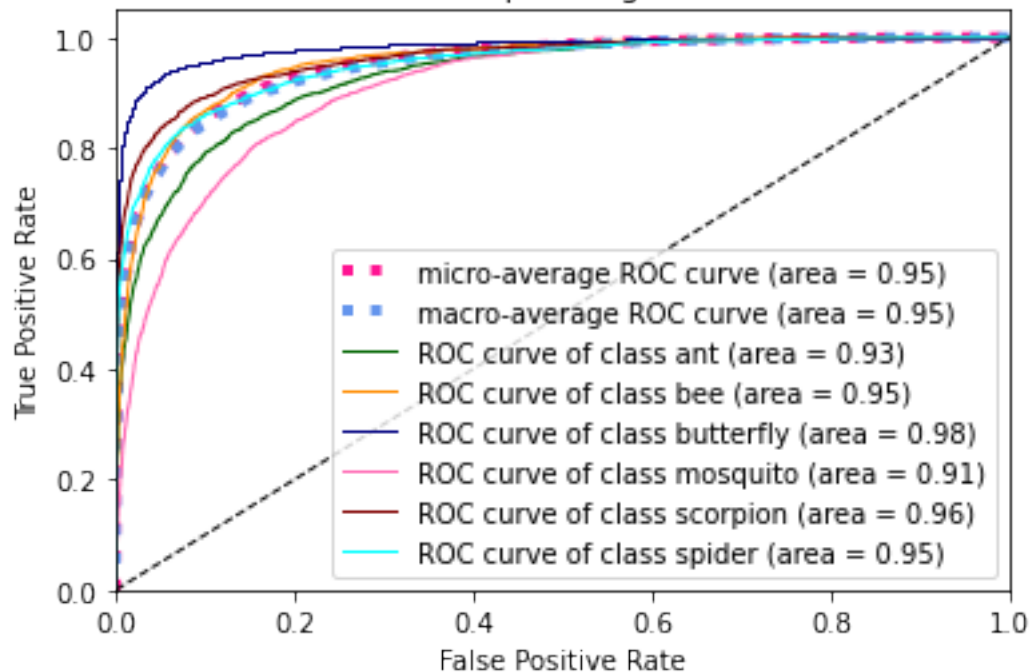


Test loss: 0.7577

	precision	recall	f1-score	support
ant	0.72	0.67	0.70	2478
bee	0.74	0.78	0.76	2488
butterfly	0.94	0.82	0.88	2557
mosquito	0.59	0.69	0.64	2527
scorpion	0.80	0.81	0.80	2468
spider	0.79	0.75	0.77	2482
accuracy			0.76	15000
macro avg	0.76	0.76	0.76	15000
weighted avg	0.76	0.76	0.76	15000



Some extension of Receiver operating characteristic to multi-class



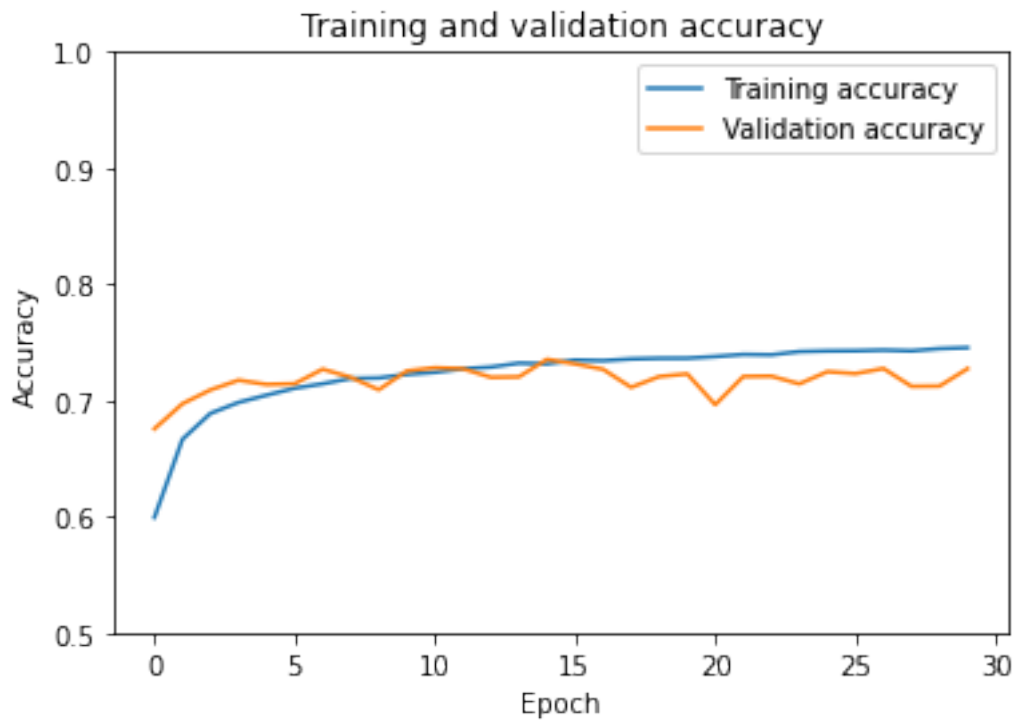
One-vs-One ROC AUC scores:  
 0.947502 (macro),  
 0.947534 (weighted by prevalence)  
 One-vs-Rest ROC AUC scores:  
 0.947521 (macro),  
 0.947577 (weighted by prevalence)

```
[ ]: model_0005L2_40do, history_0005L2_40do, score_0005L2_40do, y_pred_0005L2_40do = ↪ run_model(l2_val=0.0005, dropout=0.4)
```

Model: "Multi\_Layer\_Perceptron\_LeakyReLU\_0.4D0\_0.0005L2"

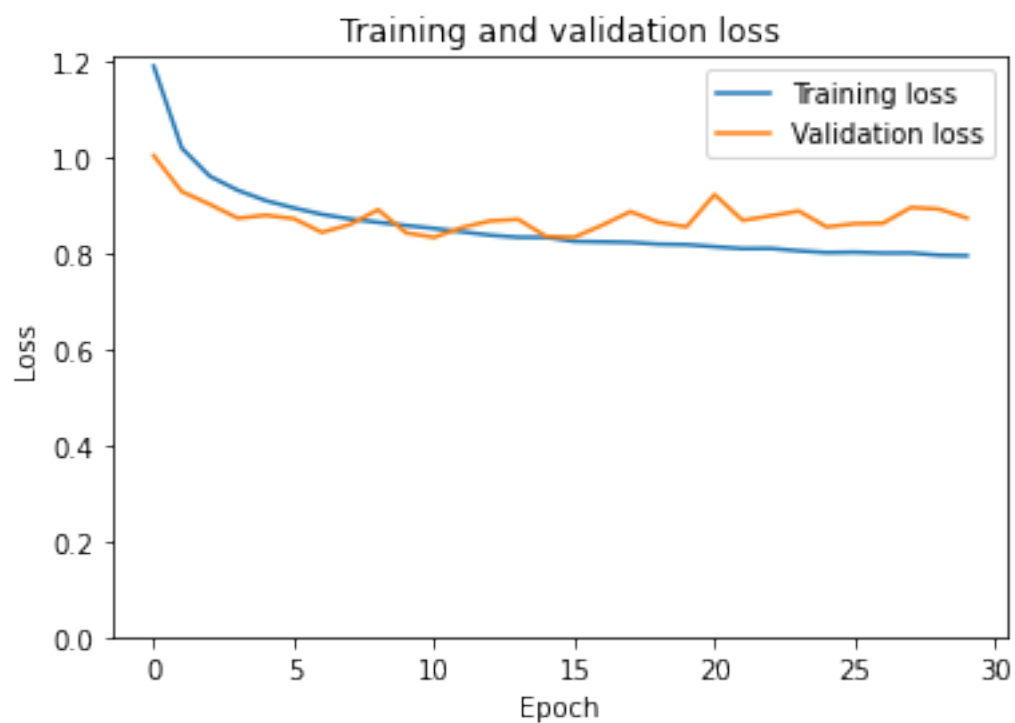
Layer (type)	Output Shape	Param #
=====		

Dense1_LeakyReLU (Dense)	(None, 32)	25120
-----		
BatchNormalization1 (BatchNo	(None, 32)	128
-----		
Dense2_LeakyReLU (Dense)	(None, 32)	1056
-----		
Dropout_0.4 (Dropout)	(None, 32)	0
-----		
Dense3_LeakyReLU (Dense)	(None, 32)	1056
-----		
Dense4_LeakyReLU (Dense)	(None, 32)	1056
-----		
BatchNormalization2 (BatchNo	(None, 32)	128
-----		
Dense5_LeakyReLU (Dense)	(None, 16)	528
-----		
Output (Dense)	(None, 6)	102
=====		
Total params: 29,174		
Trainable params: 29,046		
Non-trainable params: 128		
-----		
Total train time for 30 epochs = 74.909 seconds		



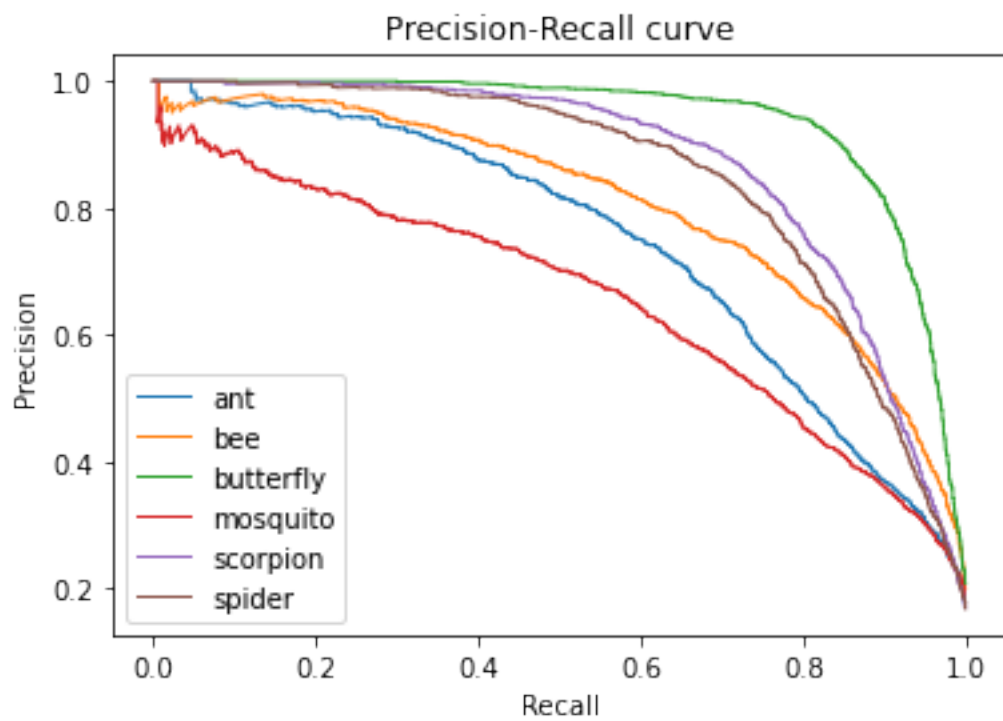
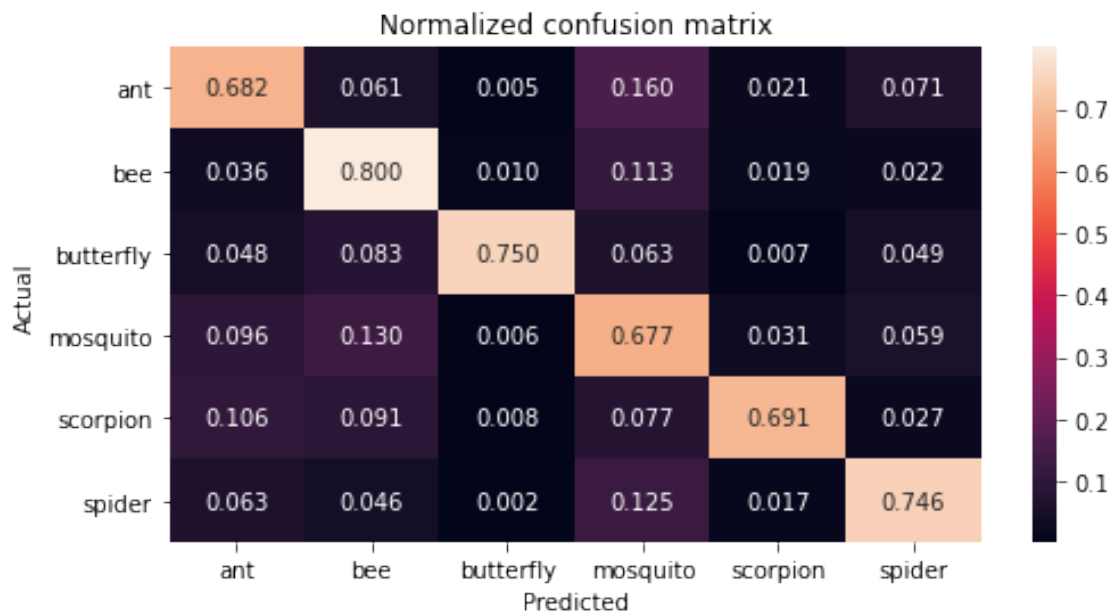


Test accuracy: 0.7245

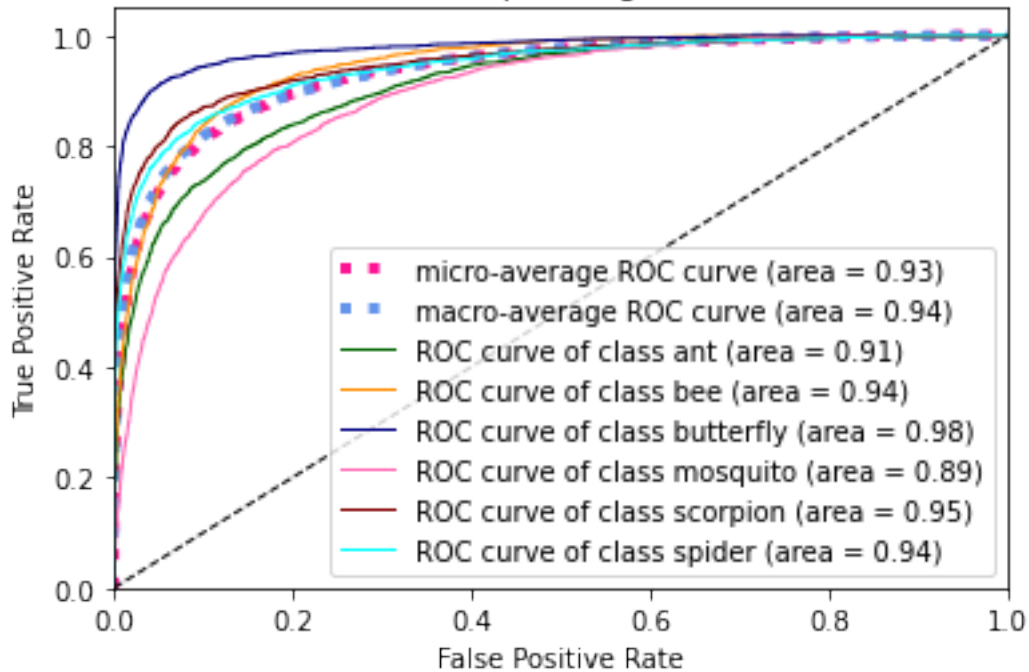


Test loss: 0.8783

	precision	recall	f1-score	support
ant	0.66	0.68	0.67	2478
bee	0.66	0.80	0.72	2488
butterfly	0.96	0.75	0.84	2557
mosquito	0.56	0.68	0.61	2527
scorpion	0.88	0.69	0.77	2468
spider	0.76	0.75	0.76	2482
accuracy			0.72	15000
macro avg	0.75	0.72	0.73	15000
weighted avg	0.75	0.72	0.73	15000



Some extension of Receiver operating characteristic to multi-class



One-vs-One ROC AUC scores:  
 0.935029 (macro),  
 0.935063 (weighted by prevalence)  
 One-vs-Rest ROC AUC scores:  
 0.935038 (macro),  
 0.935112 (weighted by prevalence)

```
[ ]: model_01L2, history_01L2, score_01L2, y_pred_01L2 = run_model(l2_val=0.01)
```

Model: "Multi\_Layer\_Perceptron\_LeakyReLU\_ODO\_0.01L2"

Layer (type)	Output Shape	Param #
Dense1_LeakyReLU (Dense)	(None, 32)	25120

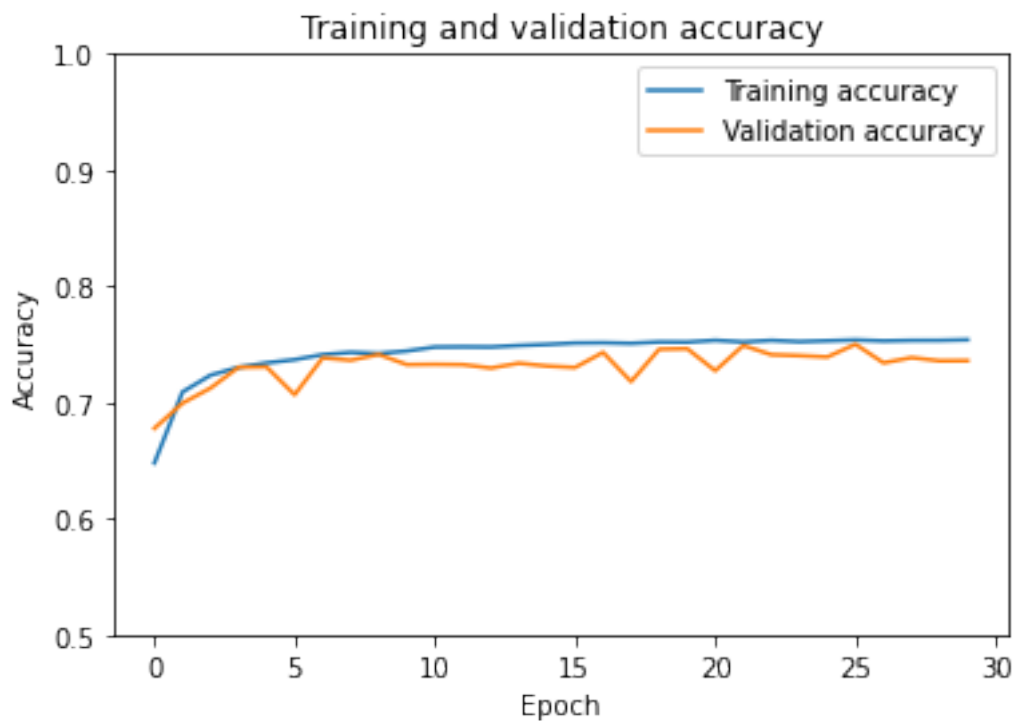
BatchNormalization1 (BatchNo	(None, 32)	128
Dense2_LeakyReLU (Dense)	(None, 32)	1056
Dropout_0 (Dropout)	(None, 32)	0
Dense3_LeakyReLU (Dense)	(None, 32)	1056
Dense4_LeakyReLU (Dense)	(None, 32)	1056
BatchNormalization2 (BatchNo	(None, 32)	128
Dense5_LeakyReLU (Dense)	(None, 16)	528
Output (Dense)	(None, 6)	102

=====

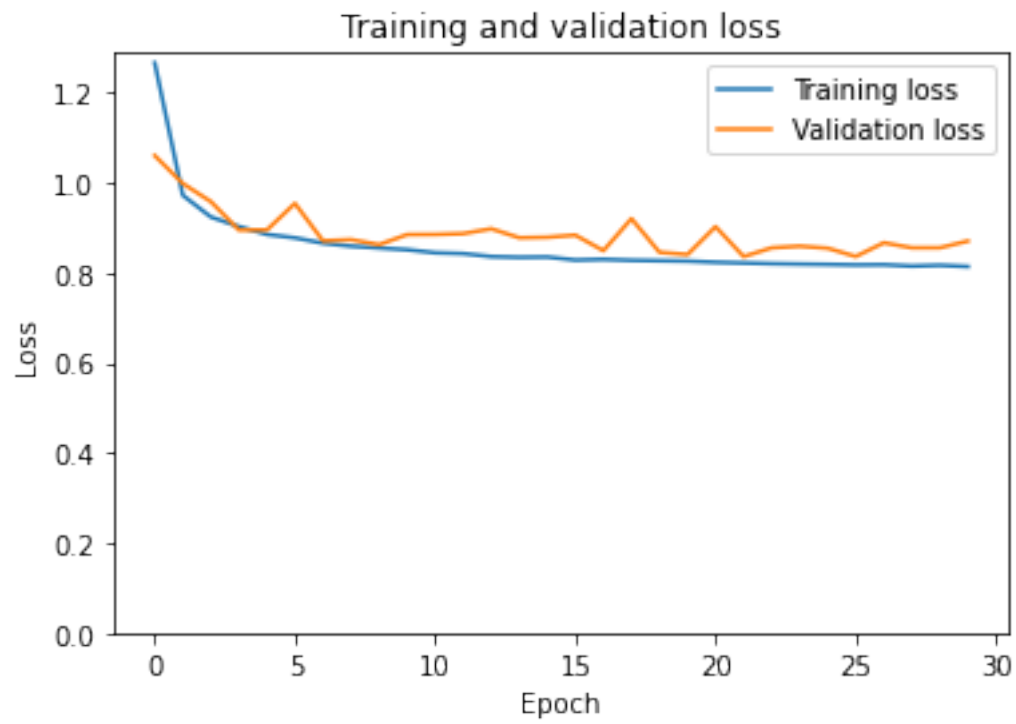
Total params: 29,174  
Trainable params: 29,046  
Non-trainable params: 128

-----

Total train time for 30 epochs = 75.891 seconds

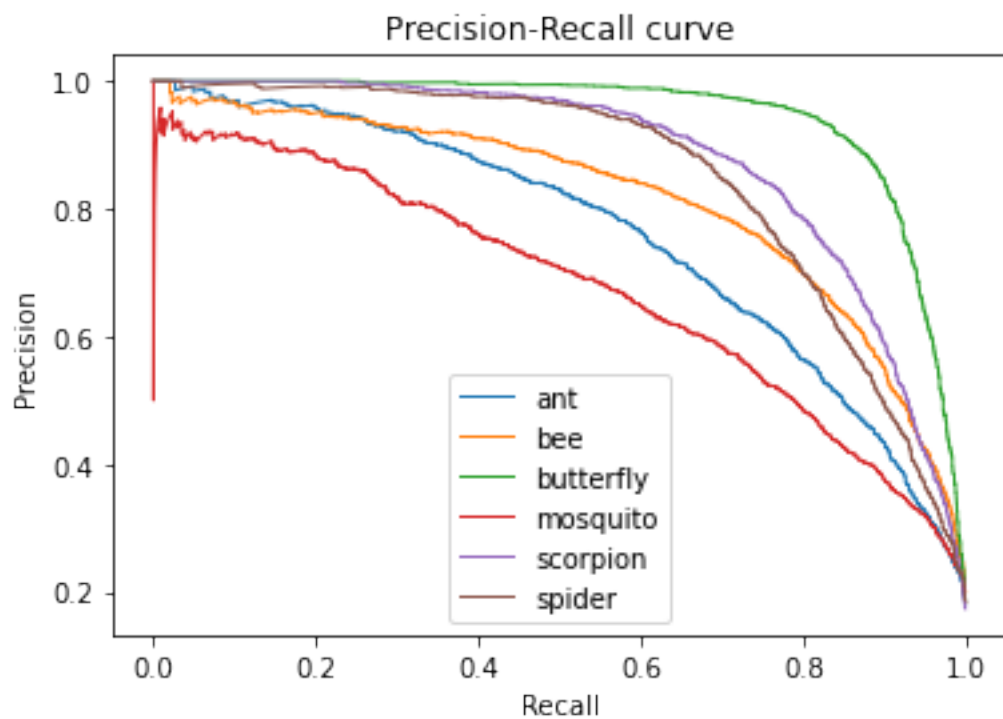
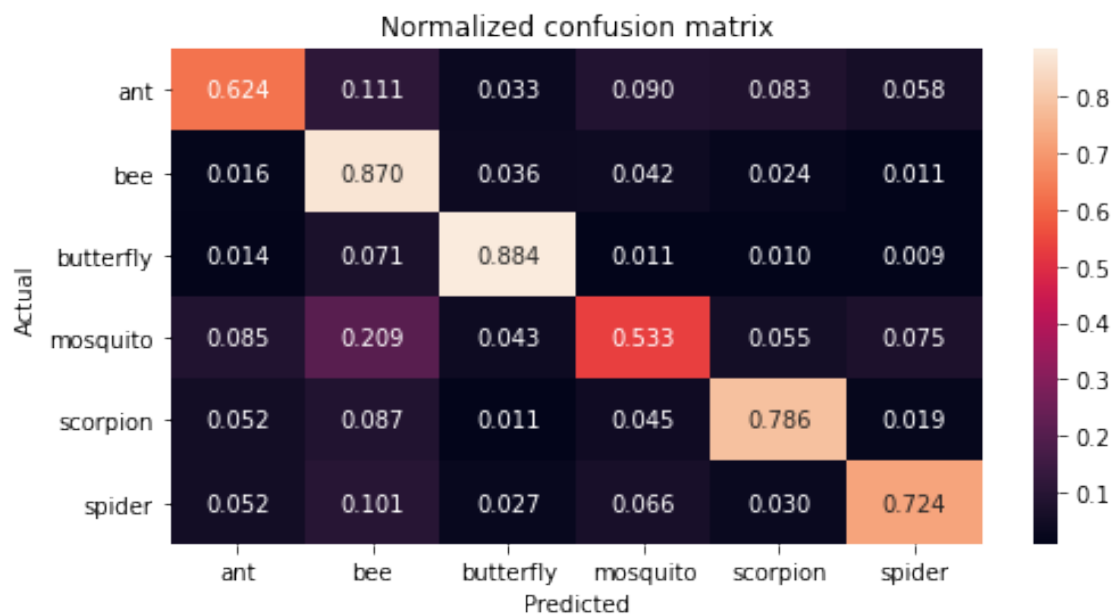


Test accuracy: 0.7371

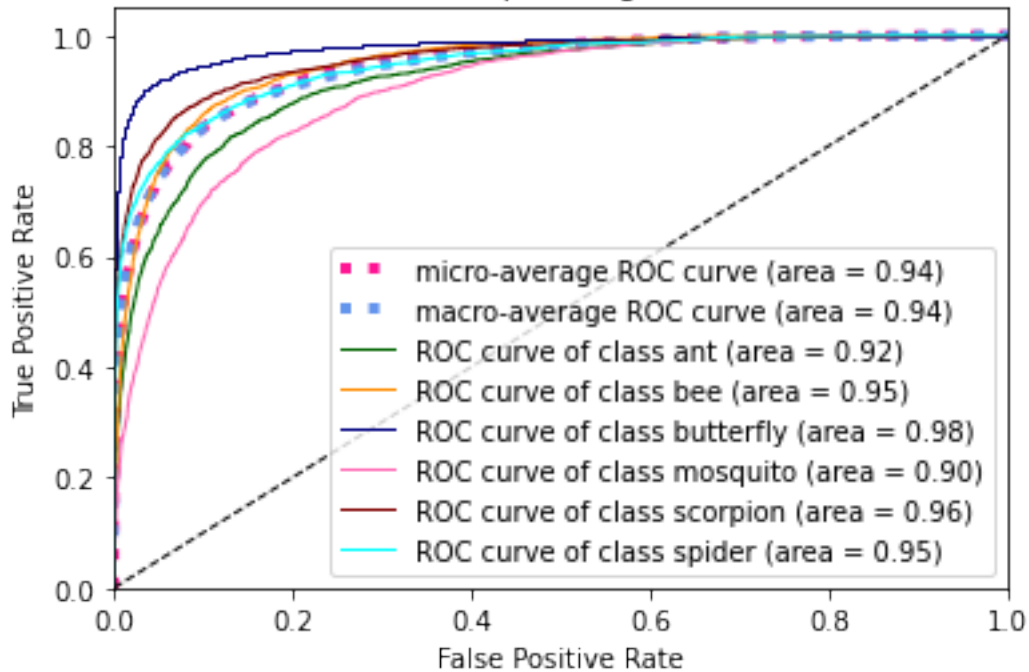


Test loss: 0.8738

	precision	recall	f1-score	support
ant	0.74	0.62	0.68	2478
bee	0.60	0.87	0.71	2488
butterfly	0.86	0.88	0.87	2557
mosquito	0.68	0.53	0.60	2527
scorpion	0.79	0.79	0.79	2468
spider	0.81	0.72	0.76	2482
accuracy			0.74	15000
macro avg	0.75	0.74	0.73	15000
weighted avg	0.75	0.74	0.73	15000



Some extension of Receiver operating characteristic to multi-class



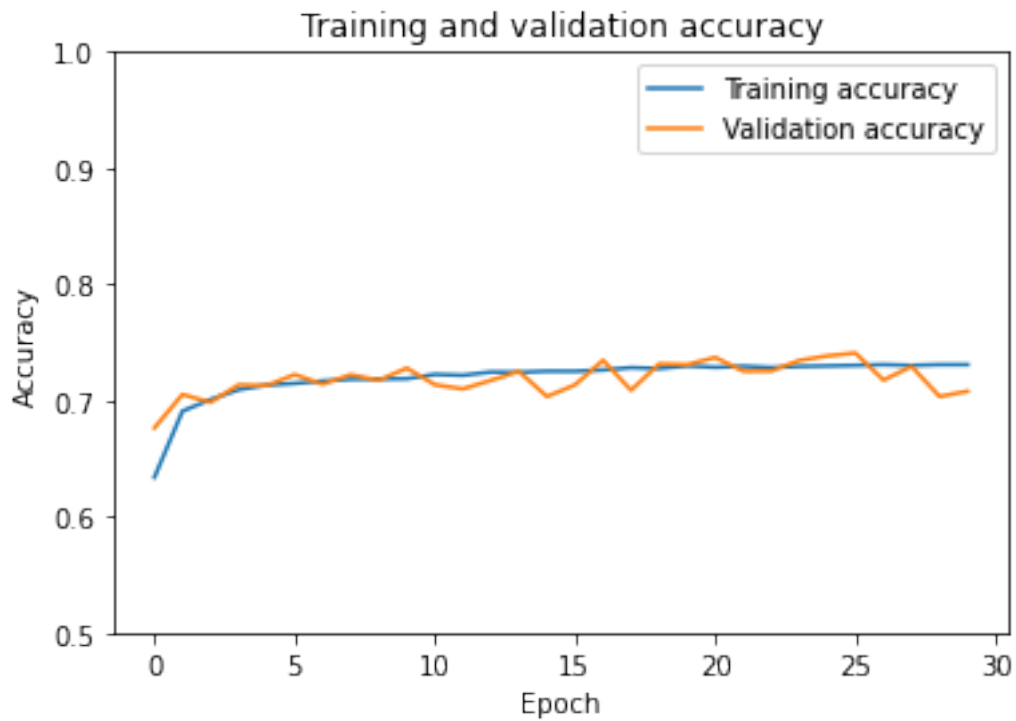
One-vs-One ROC AUC scores:  
 0.941489 (macro),  
 0.941559 (weighted by prevalence)  
 One-vs-Rest ROC AUC scores:  
 0.941585 (macro),  
 0.941641 (weighted by prevalence)

```
[ ]: model_01L2_10do, history_01L2_10do, score_01L2_10do, y_pred_01L2_10do = run_model(l2_val=0.01, dropout=0.1)
```

Model: "Multi\_Layer\_Perceptron\_LeakyReLU\_0.1D0\_0.01L2"

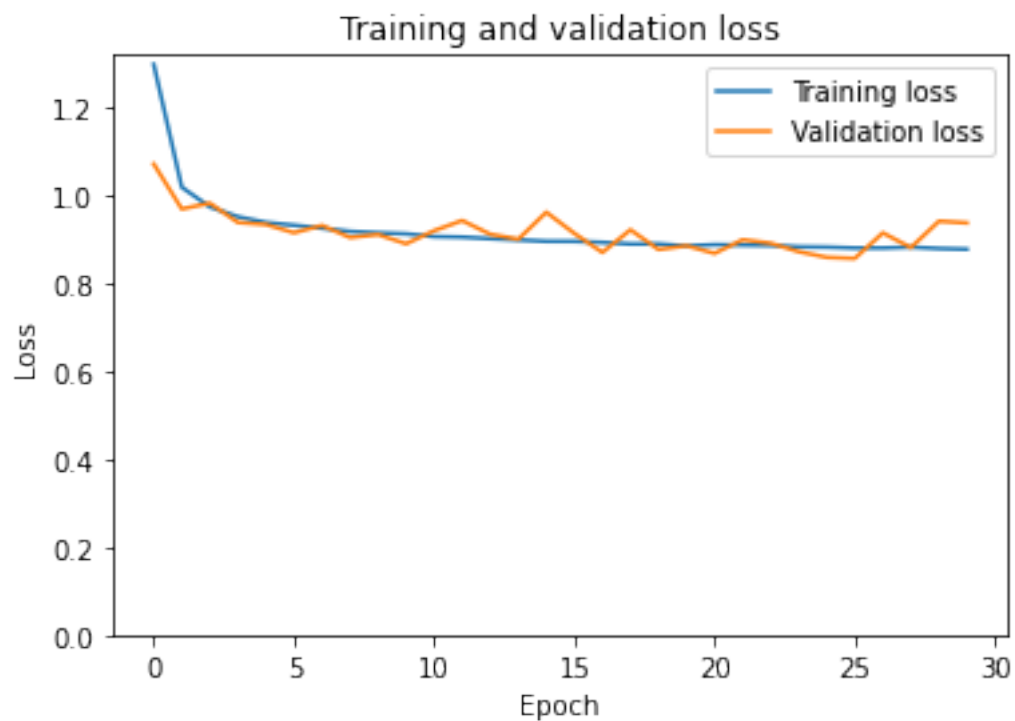
Layer (type)	Output Shape	Param #
=====		

Dense1_LeakyReLU (Dense)	(None, 32)	25120
-----		
BatchNormalization1 (BatchNo	(None, 32)	128
-----		
Dense2_LeakyReLU (Dense)	(None, 32)	1056
-----		
Dropout_0.1 (Dropout)	(None, 32)	0
-----		
Dense3_LeakyReLU (Dense)	(None, 32)	1056
-----		
Dense4_LeakyReLU (Dense)	(None, 32)	1056
-----		
BatchNormalization2 (BatchNo	(None, 32)	128
-----		
Dense5_LeakyReLU (Dense)	(None, 16)	528
-----		
Output (Dense)	(None, 6)	102
=====		
Total params: 29,174		
Trainable params: 29,046		
Non-trainable params: 128		
-----		
Total train time for 30 epochs = 74.720 seconds		



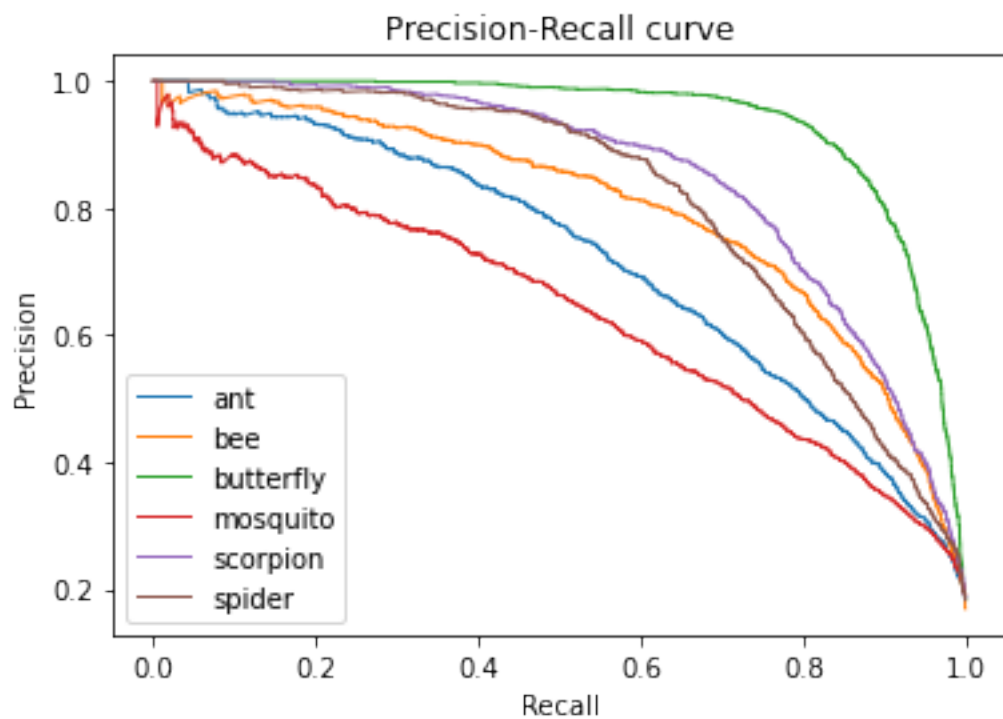
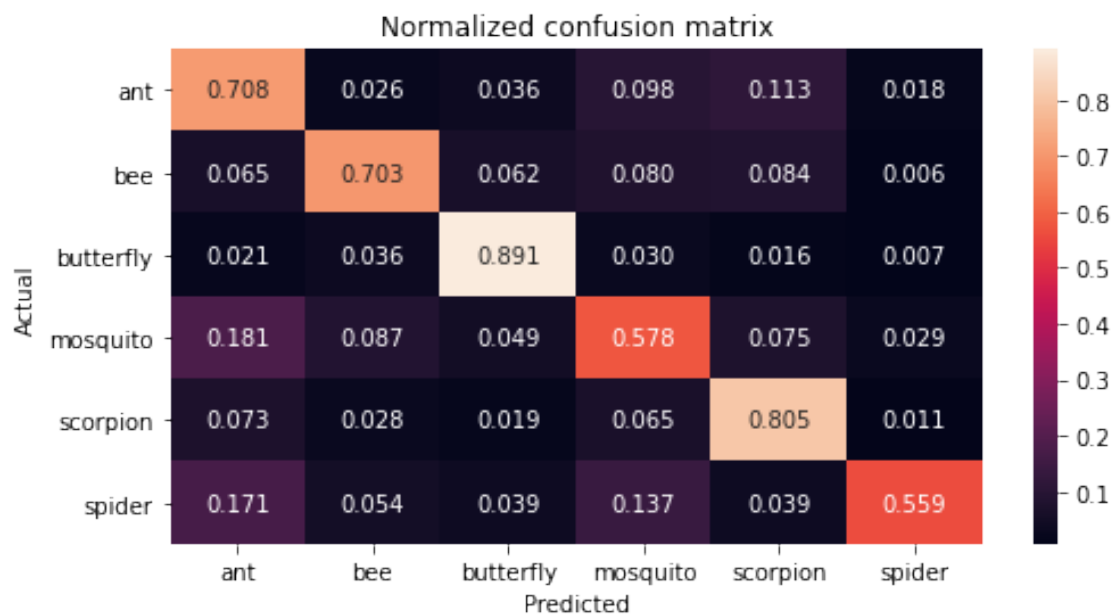


Test accuracy: 0.7078

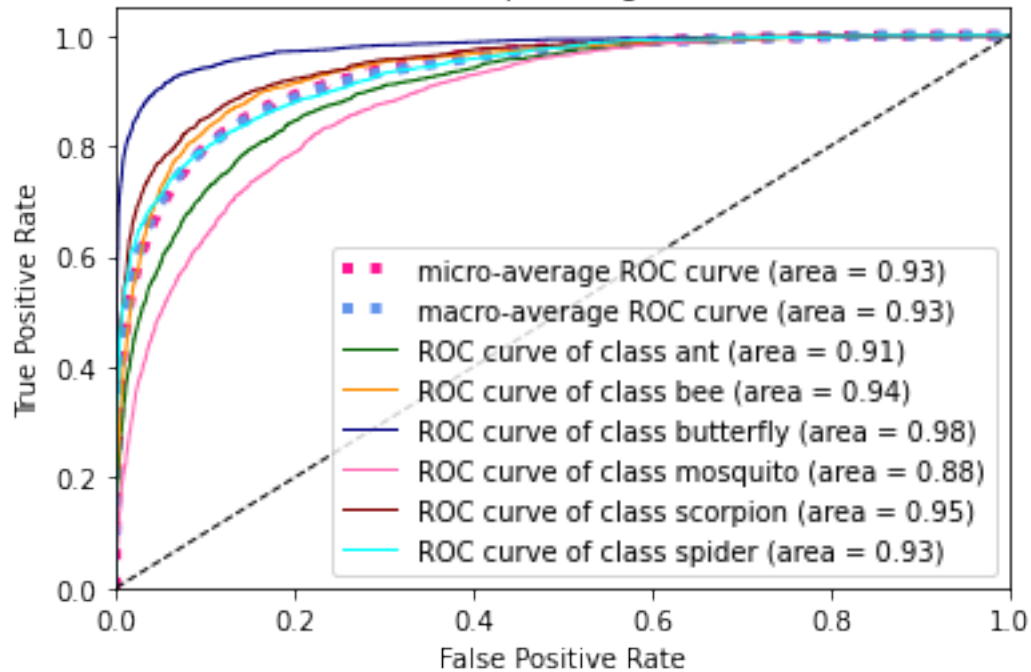


Test loss: 0.932

	precision	recall	f1-score	support
ant	0.58	0.71	0.64	2478
bee	0.75	0.70	0.73	2488
butterfly	0.82	0.89	0.85	2557
mosquito	0.59	0.58	0.58	2527
scorpion	0.71	0.80	0.75	2468
spider	0.89	0.56	0.69	2482
accuracy			0.71	15000
macro avg	0.72	0.71	0.71	15000
weighted avg	0.72	0.71	0.71	15000



Some extension of Receiver operating characteristic to multi-class



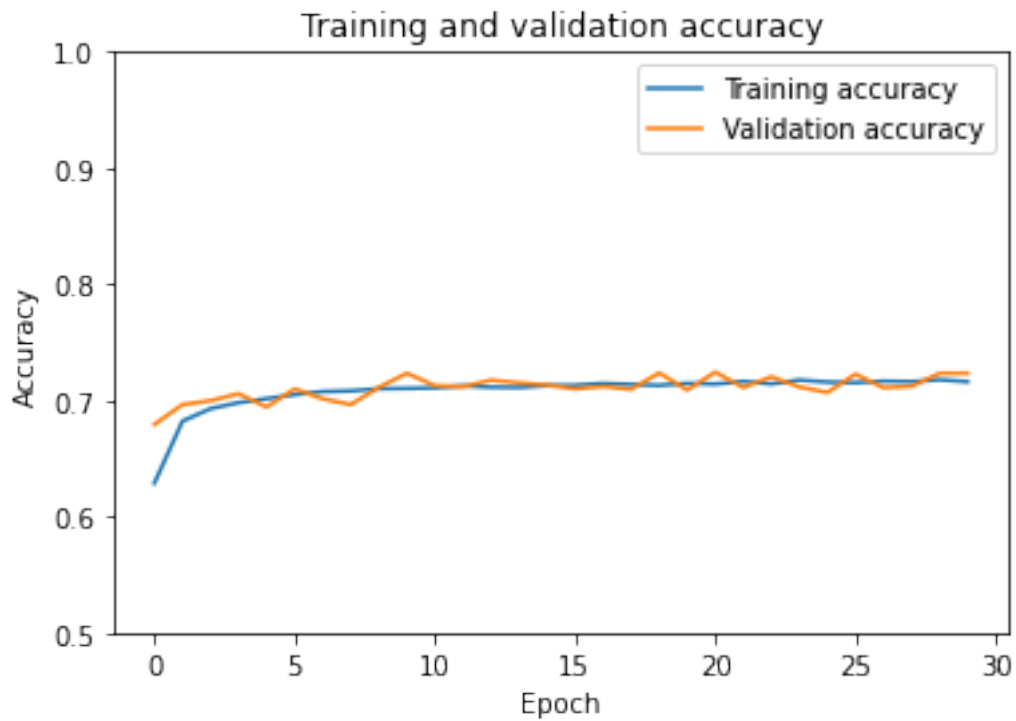
One-vs-One ROC AUC scores:  
 0.930512 (macro),  
 0.930593 (weighted by prevalence)  
 One-vs-Rest ROC AUC scores:  
 0.930607 (macro),  
 0.930690 (weighted by prevalence)

```
[ ]: model_01L2_20do, history_01L2_20do, score_01L2_20do, y_pred_01L2_20do = run_model(l2_val=0.01, dropout=0.2)
```

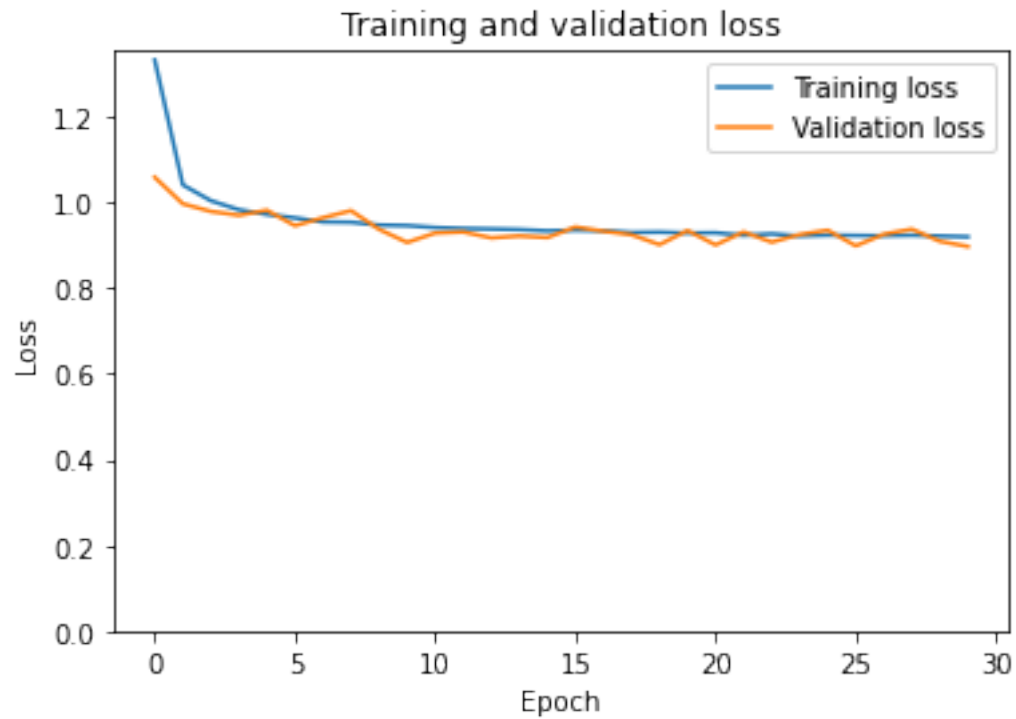
Model: "Multi\_Layer\_Perceptron\_LeakyReLU\_0.2D0\_0.01L2"

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

Dense1_LeakyReLU (Dense)	(None, 32)	25120
-----		
BatchNormalization1 (BatchNo	(None, 32)	128
-----		
Dense2_LeakyReLU (Dense)	(None, 32)	1056
-----		
Dropout_0.2 (Dropout)	(None, 32)	0
-----		
Dense3_LeakyReLU (Dense)	(None, 32)	1056
-----		
Dense4_LeakyReLU (Dense)	(None, 32)	1056
-----		
BatchNormalization2 (BatchNo	(None, 32)	128
-----		
Dense5_LeakyReLU (Dense)	(None, 16)	528
-----		
Output (Dense)	(None, 6)	102
=====		
Total params: 29,174		
Trainable params: 29,046		
Non-trainable params: 128		
-----		
Total train time for 30 epochs = 74.767 seconds		

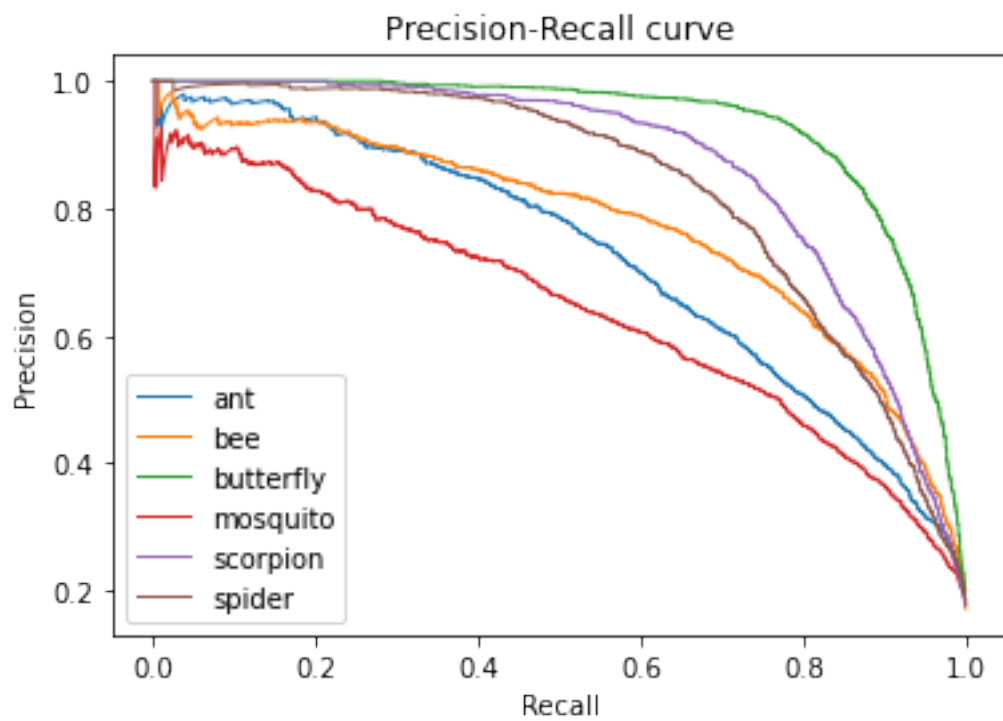
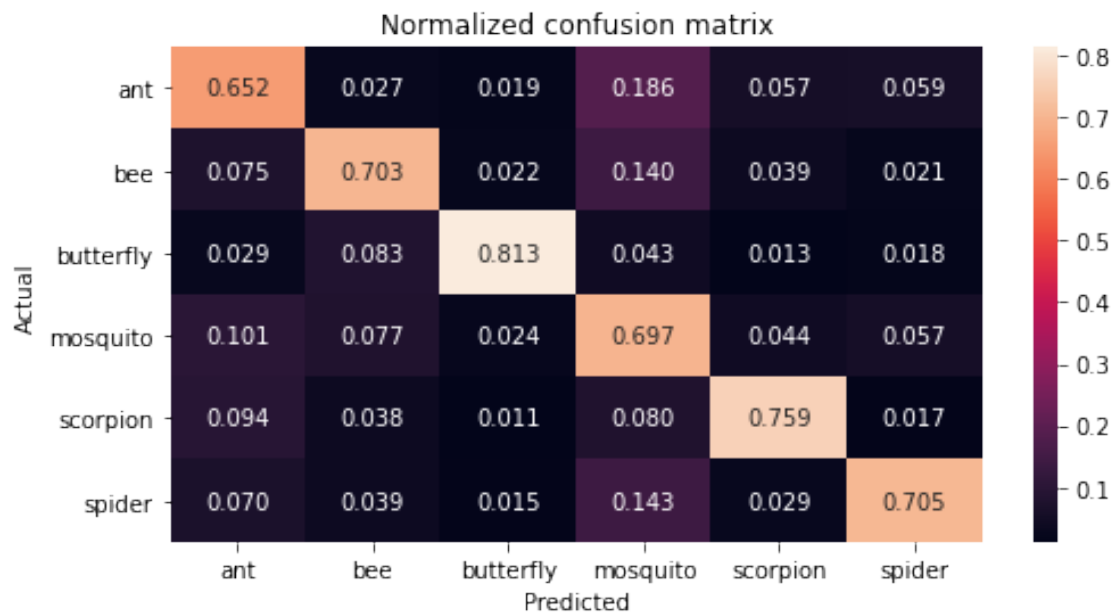


Test accuracy: 0.722

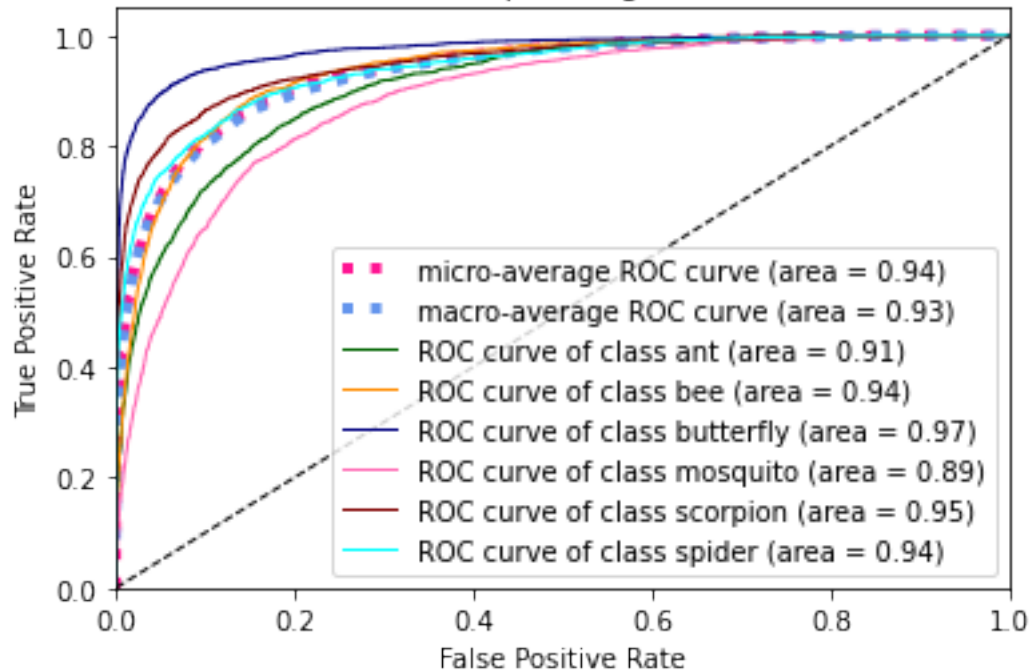


Test loss: 0.9059

	precision	recall	f1-score	support
ant	0.64	0.65	0.64	2478
bee	0.72	0.70	0.71	2488
butterfly	0.90	0.81	0.86	2557
mosquito	0.55	0.70	0.61	2527
scorpion	0.81	0.76	0.78	2468
spider	0.80	0.70	0.75	2482
accuracy			0.72	15000
macro avg	0.74	0.72	0.73	15000
weighted avg	0.74	0.72	0.73	15000



Some extension of Receiver operating characteristic to multi-class



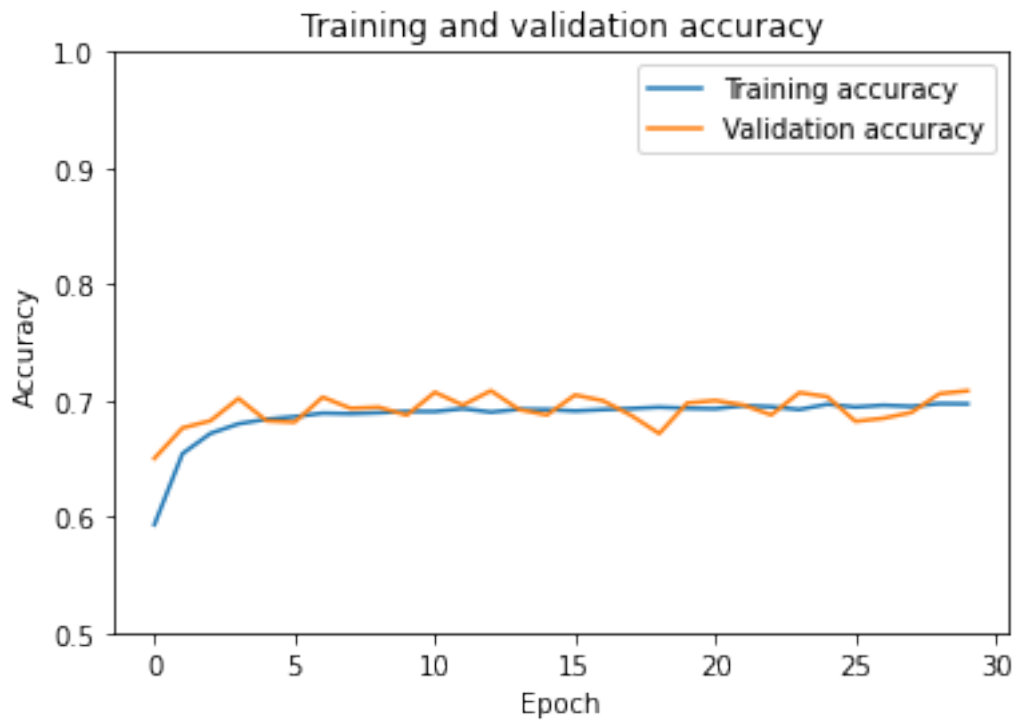
One-vs-One ROC AUC scores:  
0.932608 (macro),  
0.932666 (weighted by prevalence)  
One-vs-Rest ROC AUC scores:  
0.932675 (macro),  
0.932737 (weighted by prevalence)

```
[ ]: model_01L2_40do, history_01L2_40do, score_01L2_40do, y_pred_01L2_40do = ↪ run_model(l2_val=0.01, dropout=0.4)
```

Model: "Multi\_Layer\_Perceptron\_LeakyReLU\_0.4D0\_0.01L2"

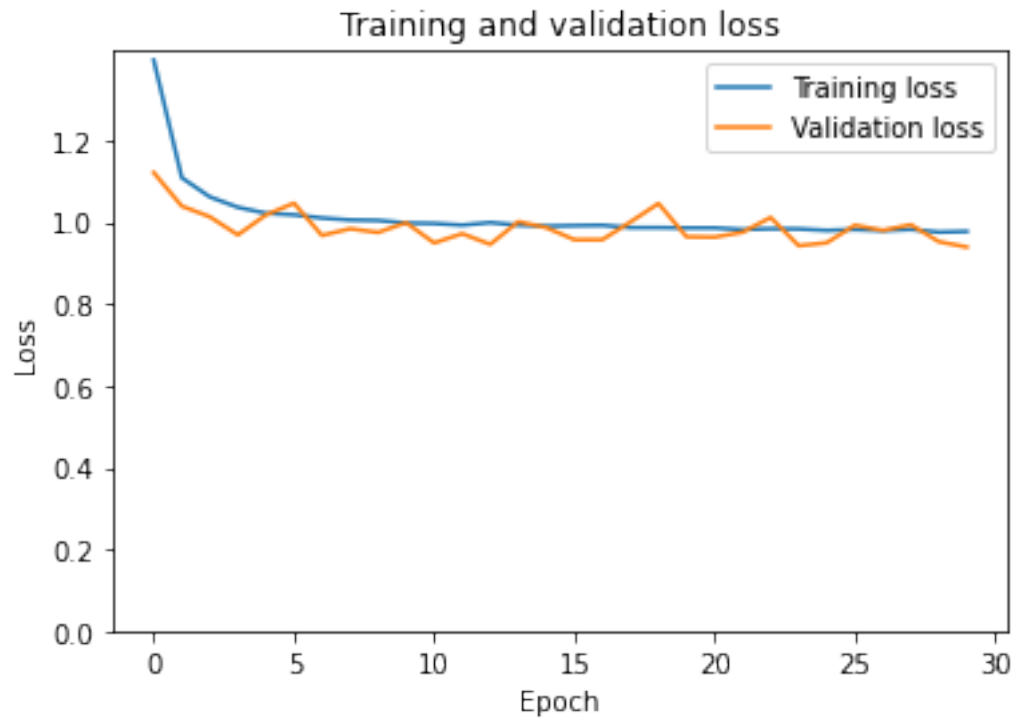
Layer (type)	Output Shape	Param #
=====		

Dense1_LeakyReLU (Dense)	(None, 32)	25120
-----		
BatchNormalization1 (BatchNo	(None, 32)	128
-----		
Dense2_LeakyReLU (Dense)	(None, 32)	1056
-----		
Dropout_0.4 (Dropout)	(None, 32)	0
-----		
Dense3_LeakyReLU (Dense)	(None, 32)	1056
-----		
Dense4_LeakyReLU (Dense)	(None, 32)	1056
-----		
BatchNormalization2 (BatchNo	(None, 32)	128
-----		
Dense5_LeakyReLU (Dense)	(None, 16)	528
-----		
Output (Dense)	(None, 6)	102
=====		
Total params: 29,174		
Trainable params: 29,046		
Non-trainable params: 128		
-----		
Total train time for 30 epochs = 75.503 seconds		



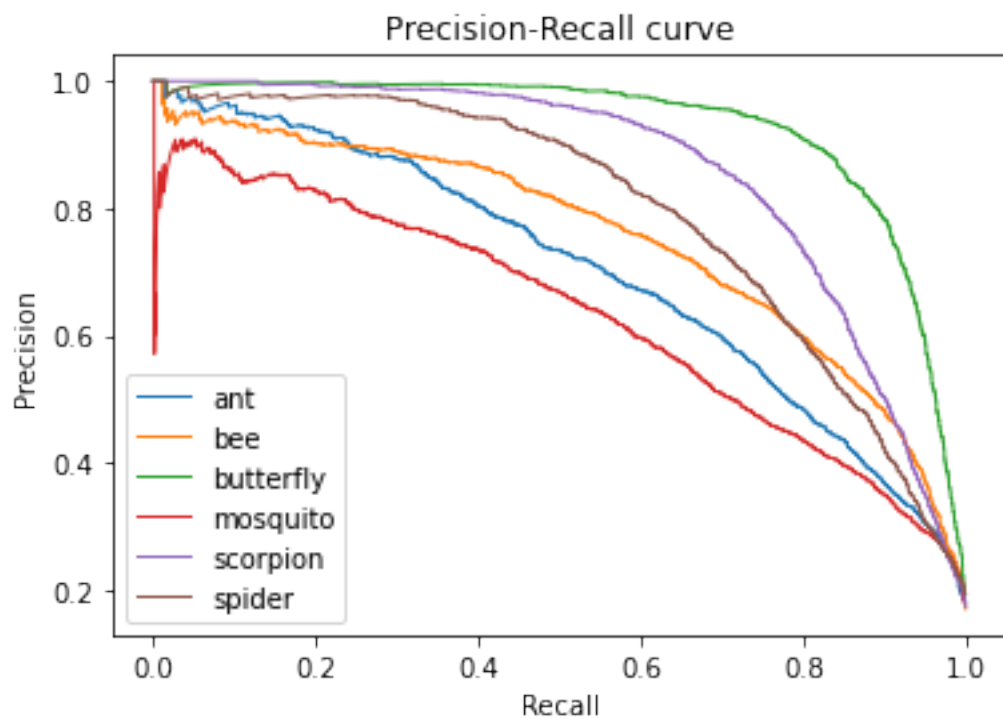
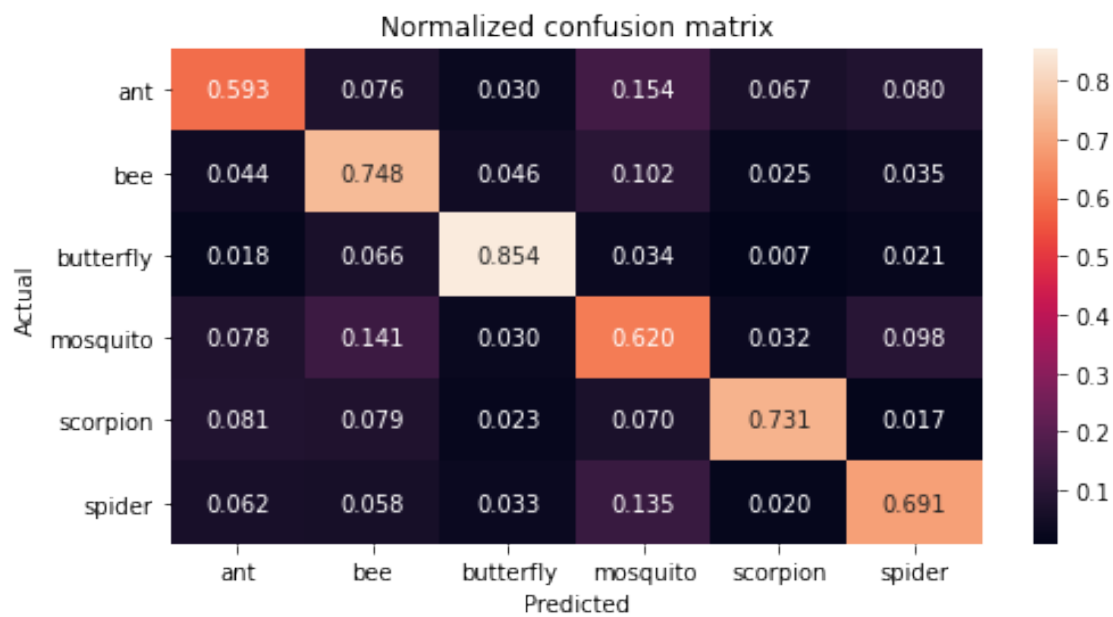


Test accuracy: 0.7068

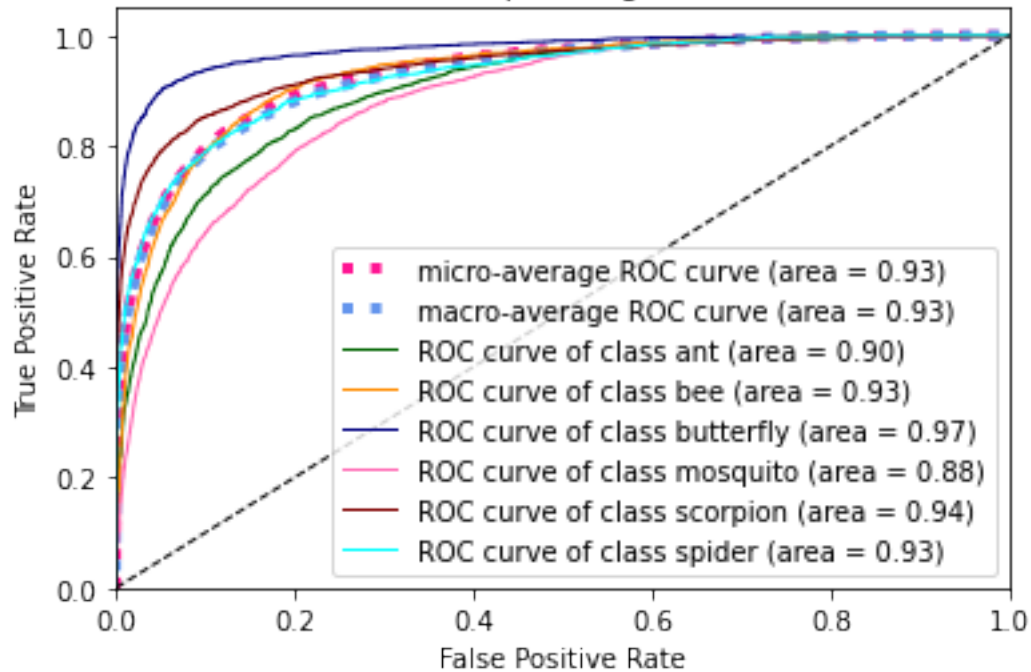


Test loss: 0.9366

	precision	recall	f1-score	support
ant	0.68	0.59	0.63	2478
bee	0.64	0.75	0.69	2488
butterfly	0.84	0.85	0.85	2557
mosquito	0.56	0.62	0.59	2527
scorpion	0.83	0.73	0.78	2468
spider	0.73	0.69	0.71	2482
accuracy			0.71	15000
macro avg	0.71	0.71	0.71	15000
weighted avg	0.71	0.71	0.71	15000



Some extension of Receiver operating characteristic to multi-class



One-vs-One ROC AUC scores:  
0.925344 (macro),  
0.925445 (weighted by prevalence)  
One-vs-Rest ROC AUC scores:  
0.925465 (macro),  
0.925565 (weighted by prevalence)

### 0.5.1 Time taken

```
[ ]: total_time = (time.time() - start_total_time) / 60
print(f"Total time %.3f" % total_time, "minutes")
```

Total time 15.270 minutes