

3b

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0.1 CSc 84020 Neural Networks and Deep Learning, Spring 2021

Homework 2 (3b)

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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/NNDL/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
```

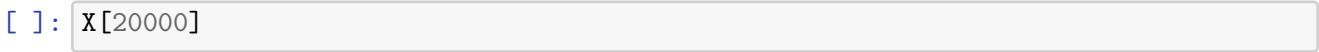
```
[ ]: start = time.time()
X, y = load_bitmaps()
print(f'\nLoading time: %.3f' % int(time.time() - start), 'seconds')
print(y[-CLASS_SAMPLE_MAX-5:-CLASS_SAMPLE_MAX+5])
```

```
ant bee butterfly mosquito scorpion spider
0 1 2 3 4 5
Loading time: 10.000 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



4

[illegible]

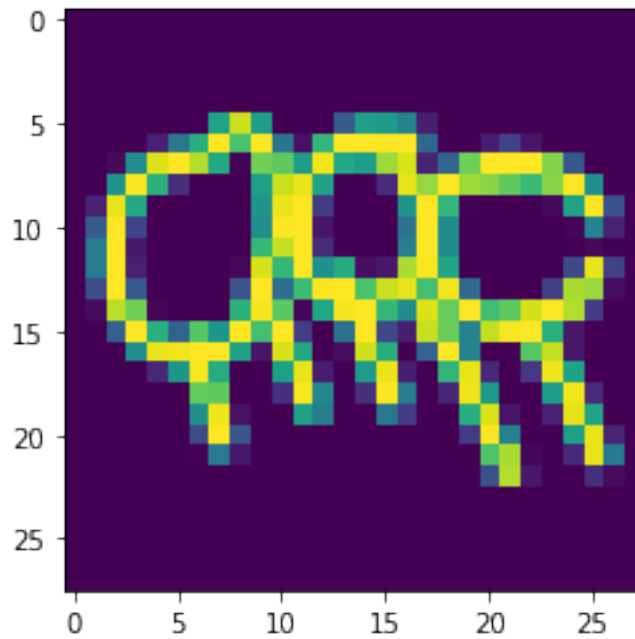
0.3 Normalization

```
[ ]: # 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.	,
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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. ,
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 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. ,

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[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 = sgd      # choose from: [sgd, Adam(lr=0.001, epsilon=1e-06)]

activation = 'relu' # 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

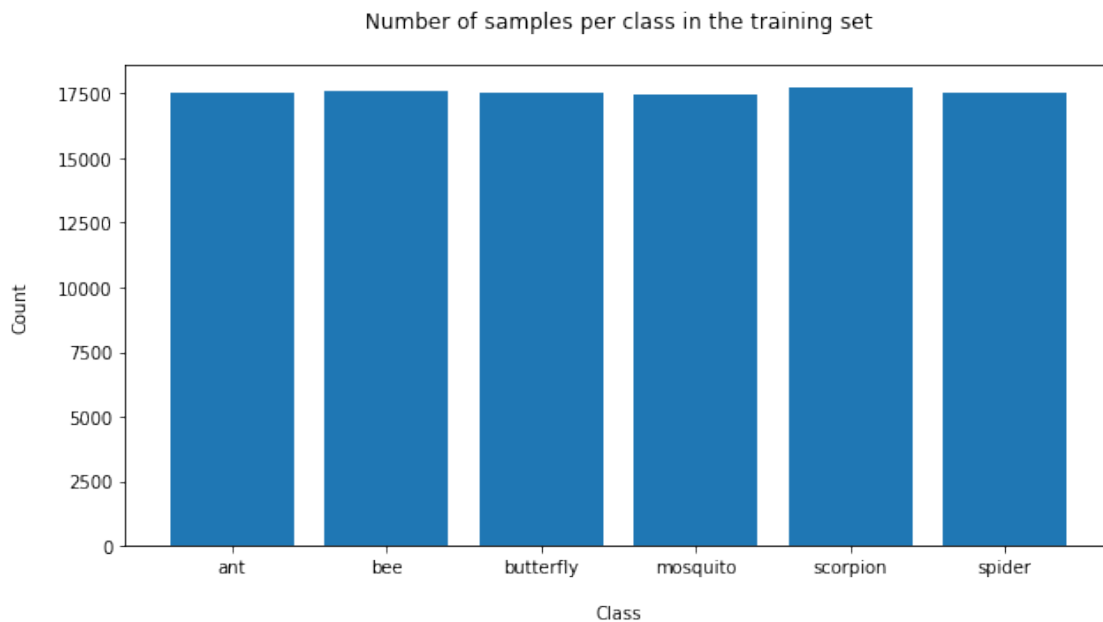
[illegible]

```
[ ]: 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)
```

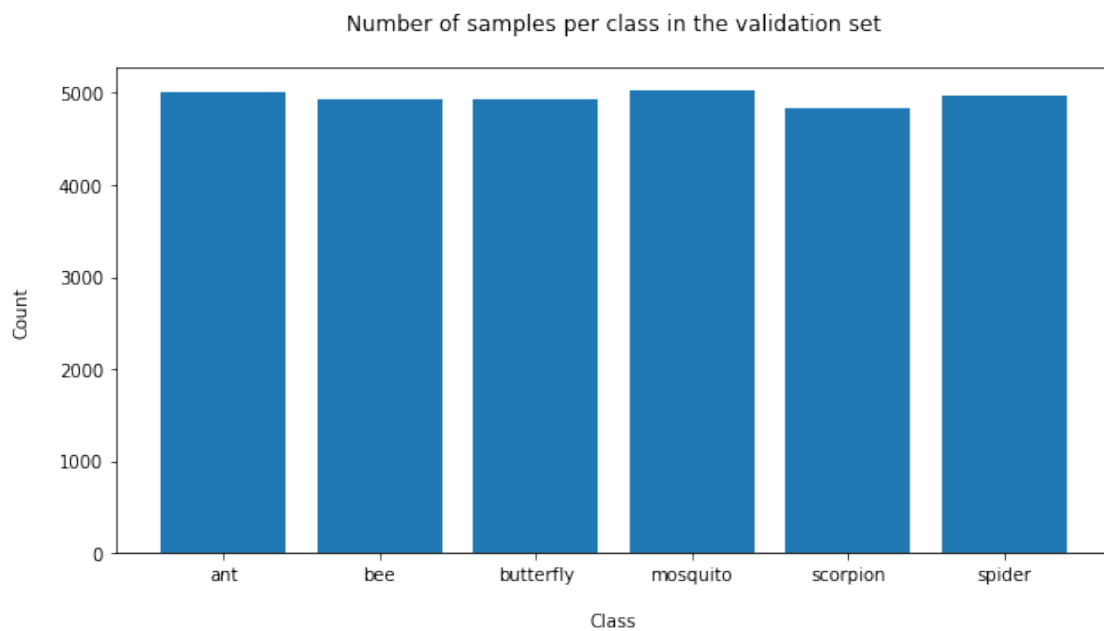
```
Number of classes: 6
Input dimension: 784
Total dataset      X:      (150000, 784)      y:      (150000,)
90.0 % train      X_train: (135000, 784)      y_train: (135000,)
10.0 % test       X_test:  (15000, 784)      y_test:  (15000,)
```

```
[ ]: # 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)
```

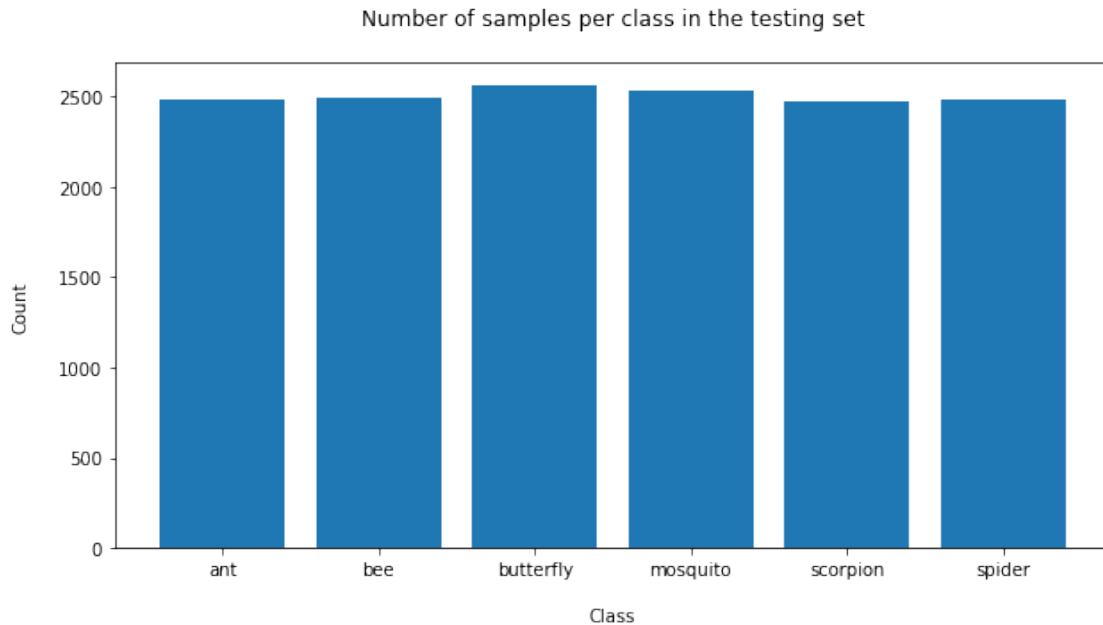
```
[ ]: # Training data
unique, counts = np.unique(Ytrain, return_counts=True)
pylab.rcParams['figure.figsize'] = (10,5)
plt.bar(critters, counts)
plt.title('Number of samples per class in the training set\n')
plt.ylabel('Count\n')
plt.xlabel('\nClass')
plt.show()
```



```
[ ]: # 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()
```

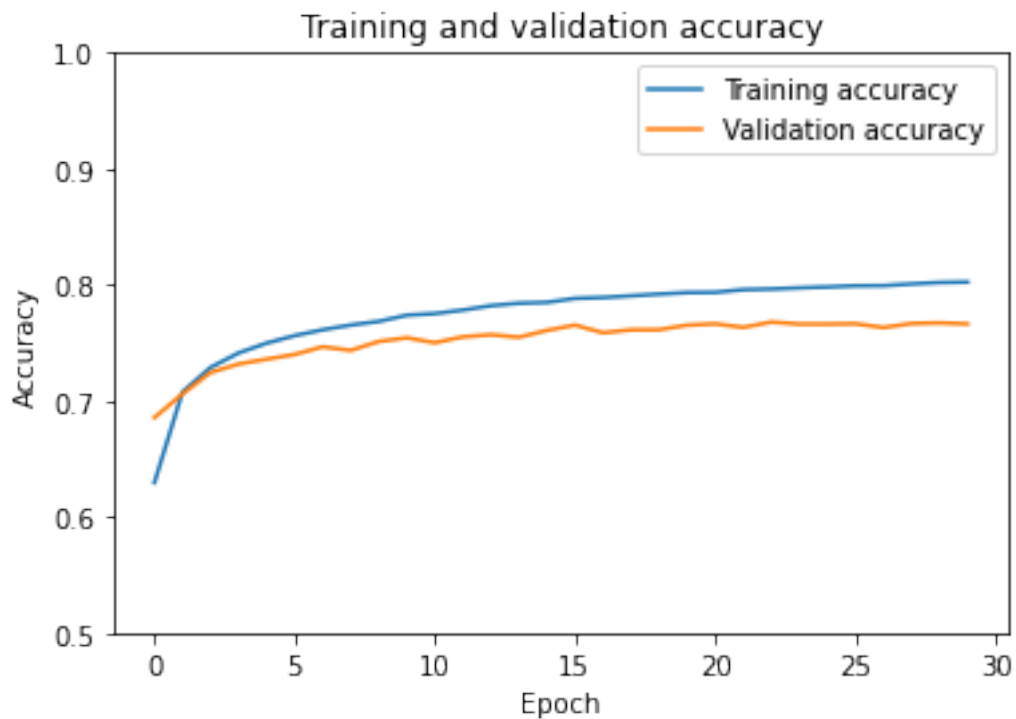
Model: "Multi_Layer_Perceptron_relu_OD0_OL2"

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

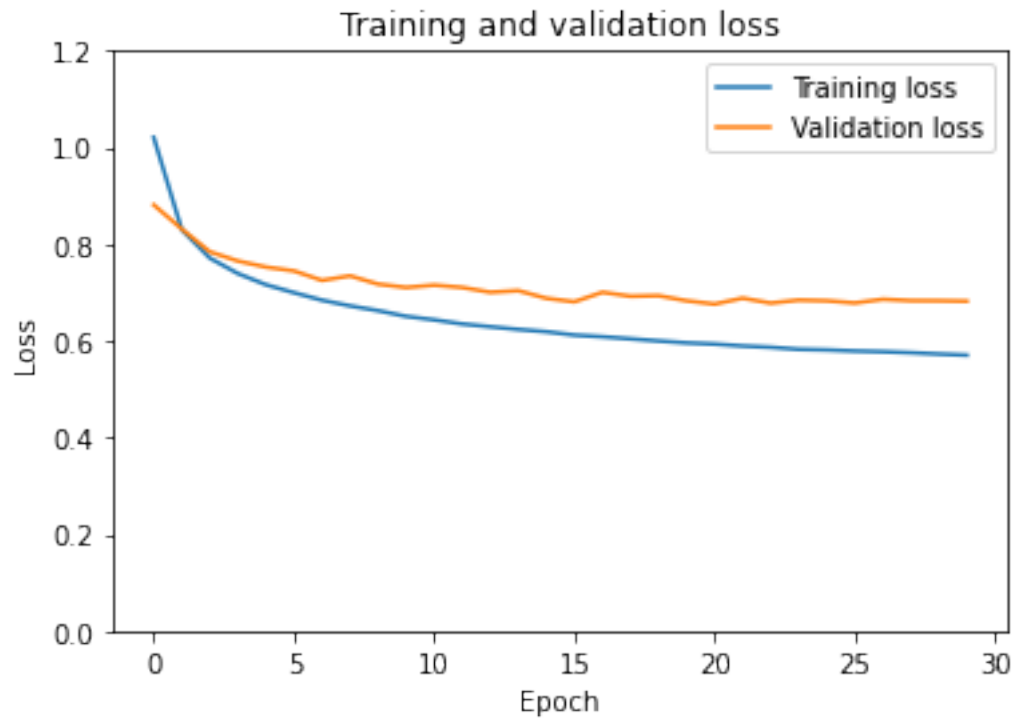
```

=====
Dense1_relu (Dense)          (None, 32)          25120
-----
BatchNormalization1 (BatchNo (None, 32)          128
-----
Dense2_relu (Dense)          (None, 32)          1056
-----
Dropout_0 (Dropout)          (None, 32)          0
-----
Dense3_relu (Dense)          (None, 32)          1056
-----
Dense4_relu (Dense)          (None, 32)          1056
-----
BatchNormalization2 (BatchNo (None, 32)          128
-----
Dense5_relu (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 = 69.571 seconds

```

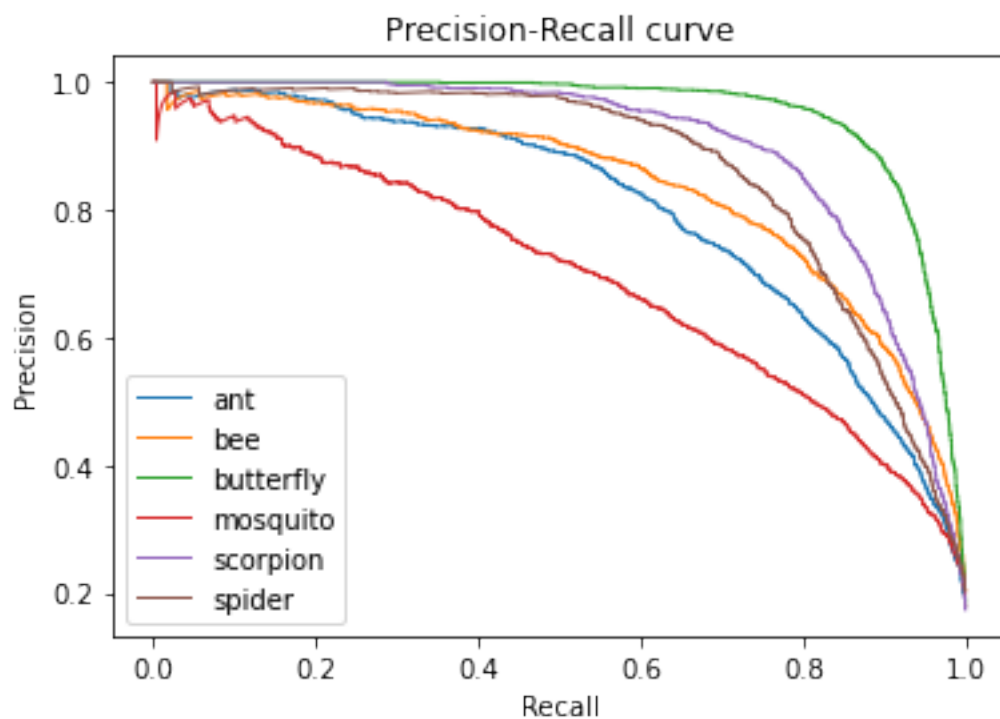
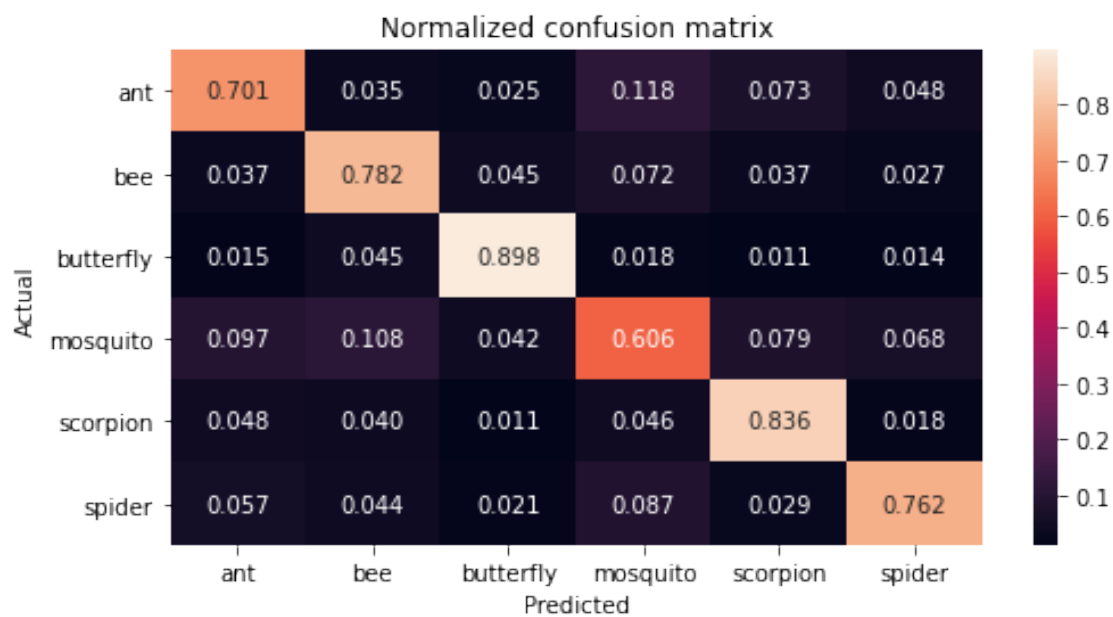


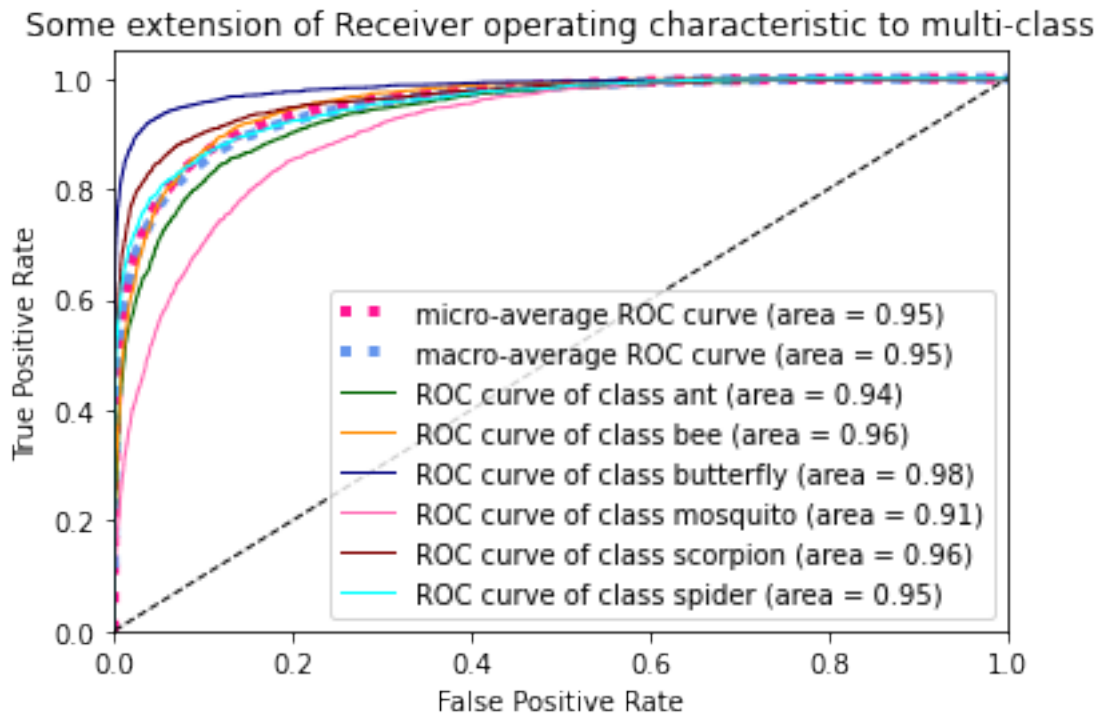
Test accuracy: 0.7644



Test loss: 0.6877

	precision	recall	f1-score	support
ant	0.73	0.70	0.72	2478
bee	0.74	0.78	0.76	2488
butterfly	0.87	0.90	0.88	2557
mosquito	0.64	0.61	0.62	2527
scorpion	0.78	0.84	0.81	2468
spider	0.81	0.76	0.79	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:
0.949499 (macro),
0.949544 (weighted by prevalence)
One-vs-Rest ROC AUC scores:
0.949564 (macro),
0.949596 (weighted by prevalence)

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

Model: "Multi_Layer_Perceptron_relu_0.1D0_OL2"

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

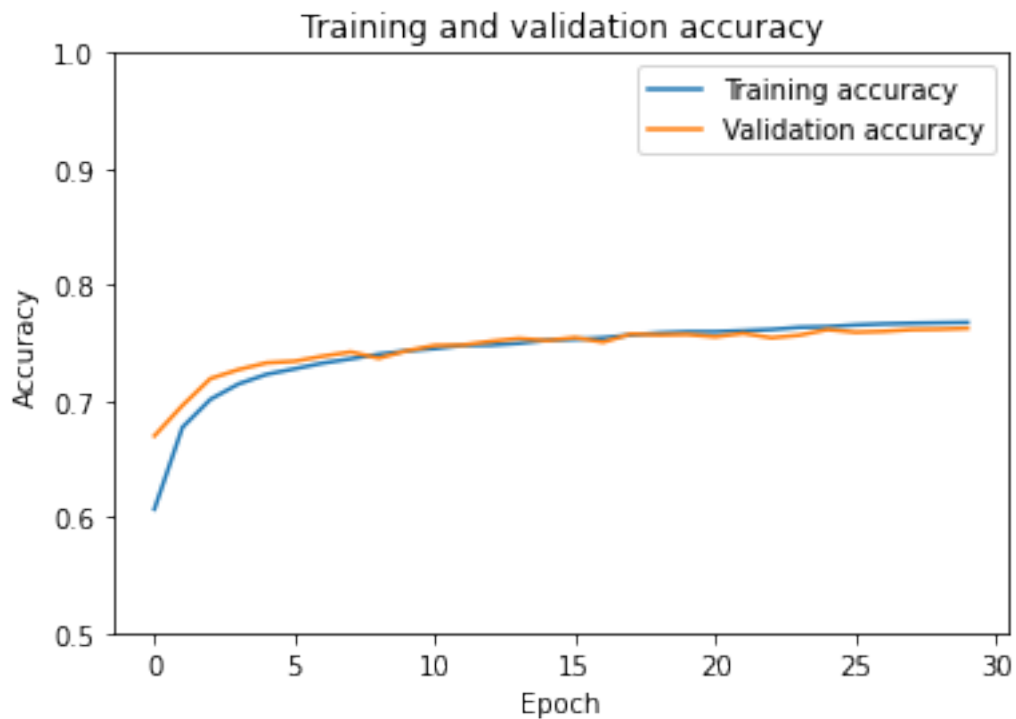
Dense1_relu (Dense)	(None, 32)	25120
BatchNormalization1 (BatchNo	(None, 32)	128
Dense2_relu (Dense)	(None, 32)	1056
Dropout_0.1 (Dropout)	(None, 32)	0
Dense3_relu (Dense)	(None, 32)	1056
Dense4_relu (Dense)	(None, 32)	1056
BatchNormalization2 (BatchNo	(None, 32)	128
Dense5_relu (Dense)	(None, 16)	528
Output (Dense)	(None, 6)	102

Total params: 29,174

Trainable params: 29,046

Non-trainable params: 128

Total train time for 30 epochs = 69.171 seconds

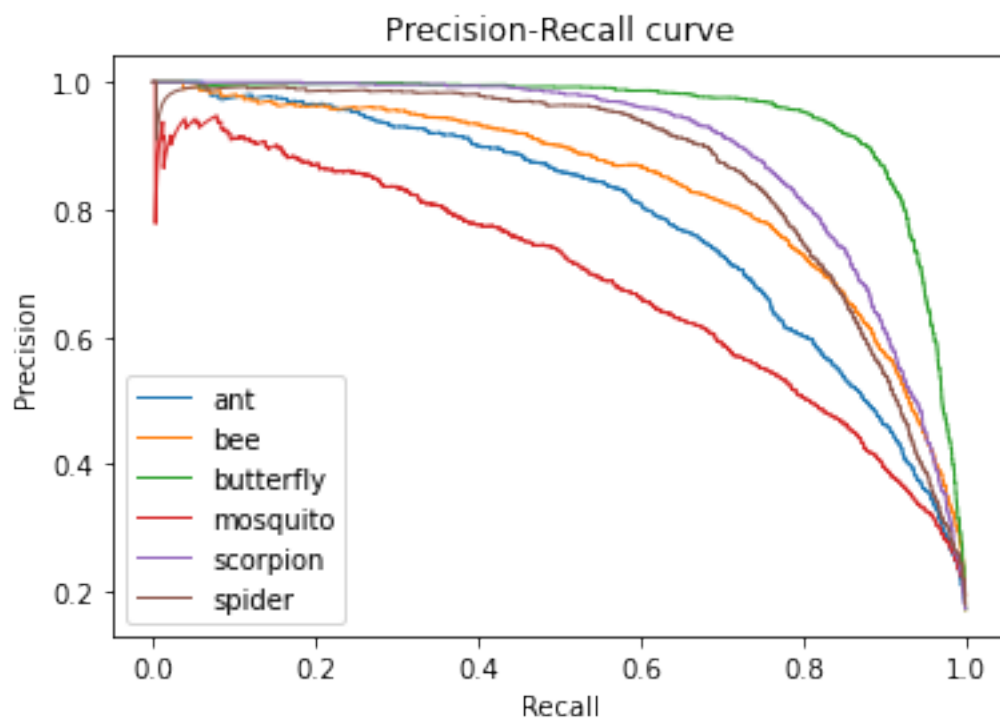
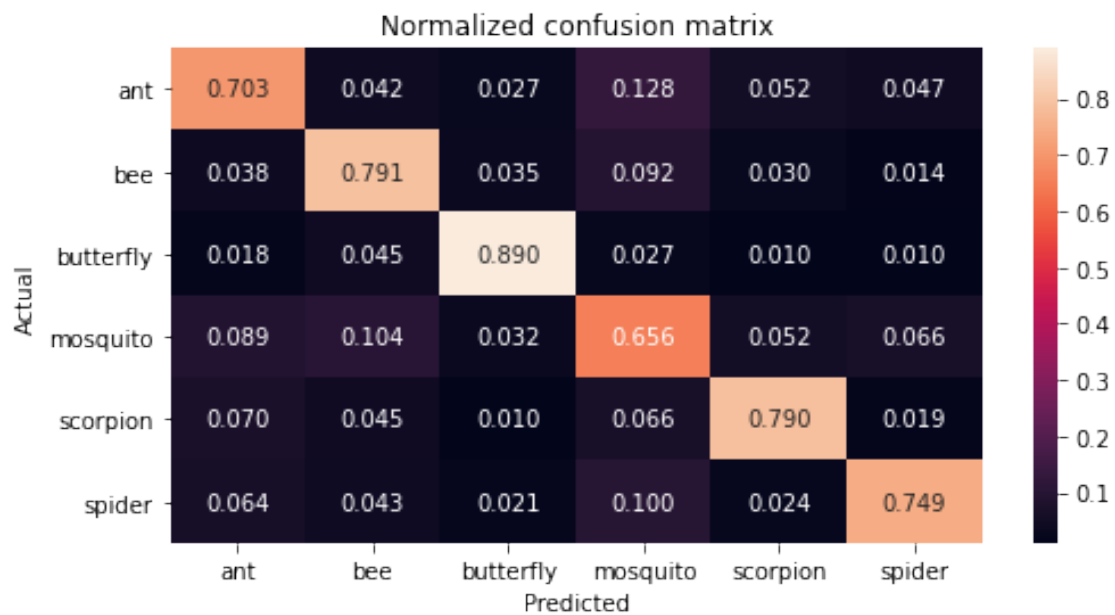


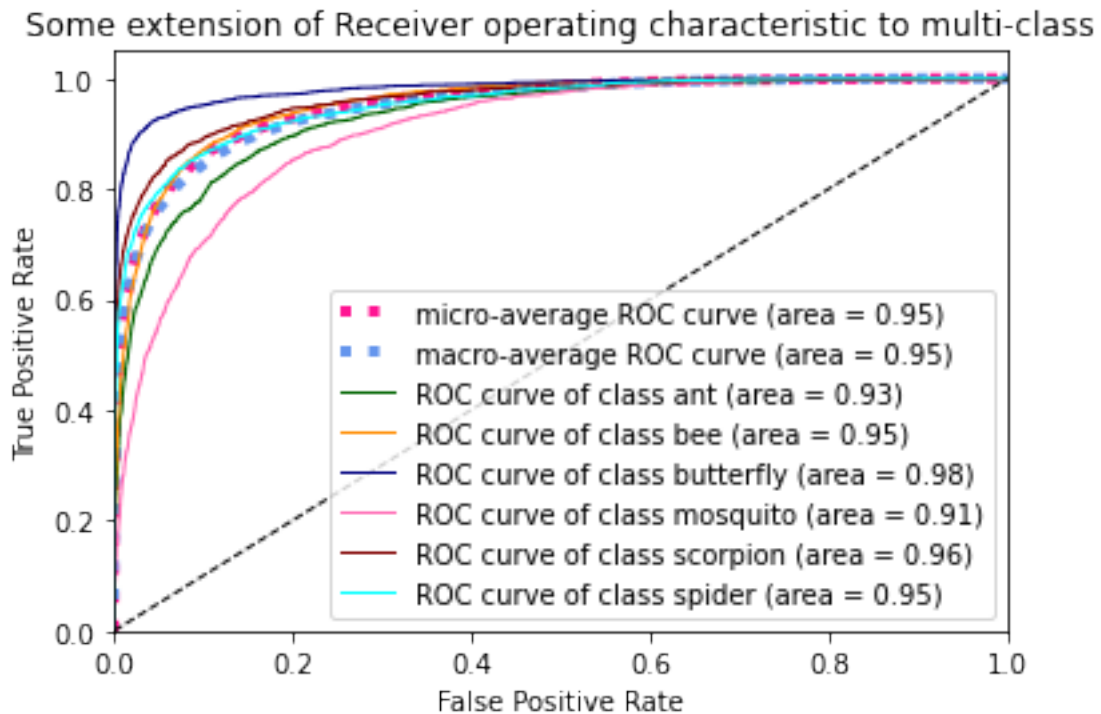
Test accuracy: 0.7634



Test loss: 0.6928

	precision	recall	f1-score	support
ant	0.71	0.70	0.71	2478
bee	0.74	0.79	0.76	2488
butterfly	0.88	0.89	0.88	2557
mosquito	0.62	0.66	0.64	2527
scorpion	0.82	0.79	0.81	2468
spider	0.83	0.75	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





One-vs-One ROC AUC scores:
0.947289 (macro),
0.947341 (weighted by prevalence)
One-vs-Rest ROC AUC scores:
0.947364 (macro),
0.947400 (weighted by prevalence)

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

Model: "Multi_Layer_Perceptron_relu_0.2D0_0L2"

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

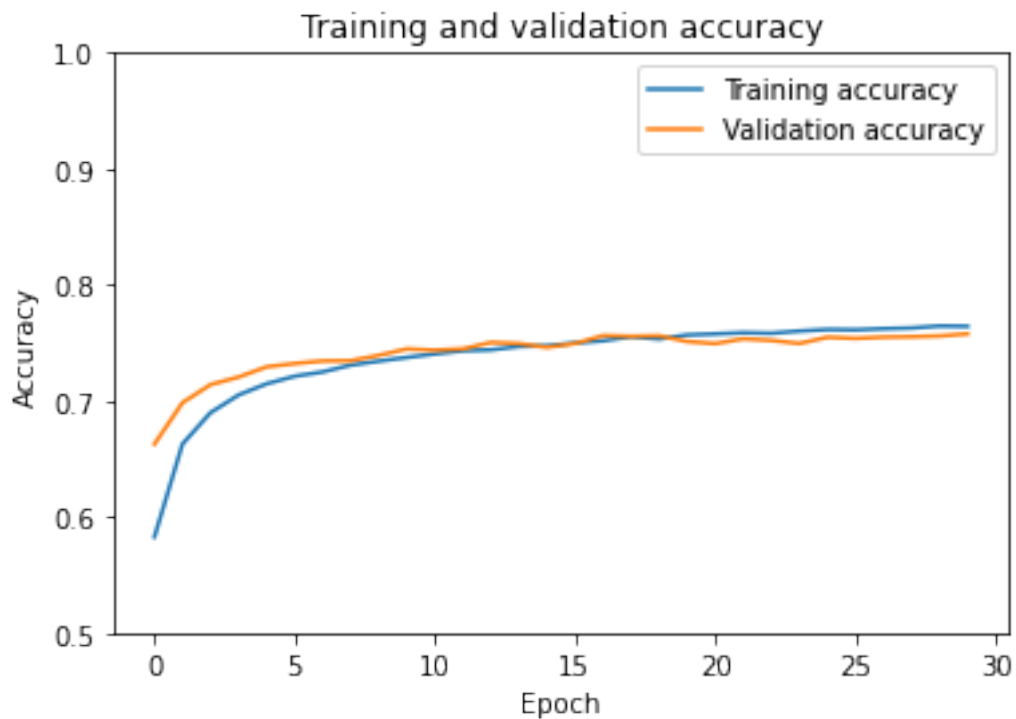
Dense1_relu (Dense)	(None, 32)	25120
BatchNormalization1 (BatchNo	(None, 32)	128
Dense2_relu (Dense)	(None, 32)	1056
Dropout_0.2 (Dropout)	(None, 32)	0
Dense3_relu (Dense)	(None, 32)	1056
Dense4_relu (Dense)	(None, 32)	1056
BatchNormalization2 (BatchNo	(None, 32)	128
Dense5_relu (Dense)	(None, 16)	528
Output (Dense)	(None, 6)	102

Total params: 29,174

Trainable params: 29,046

Non-trainable params: 128

Total train time for 30 epochs = 68.420 seconds

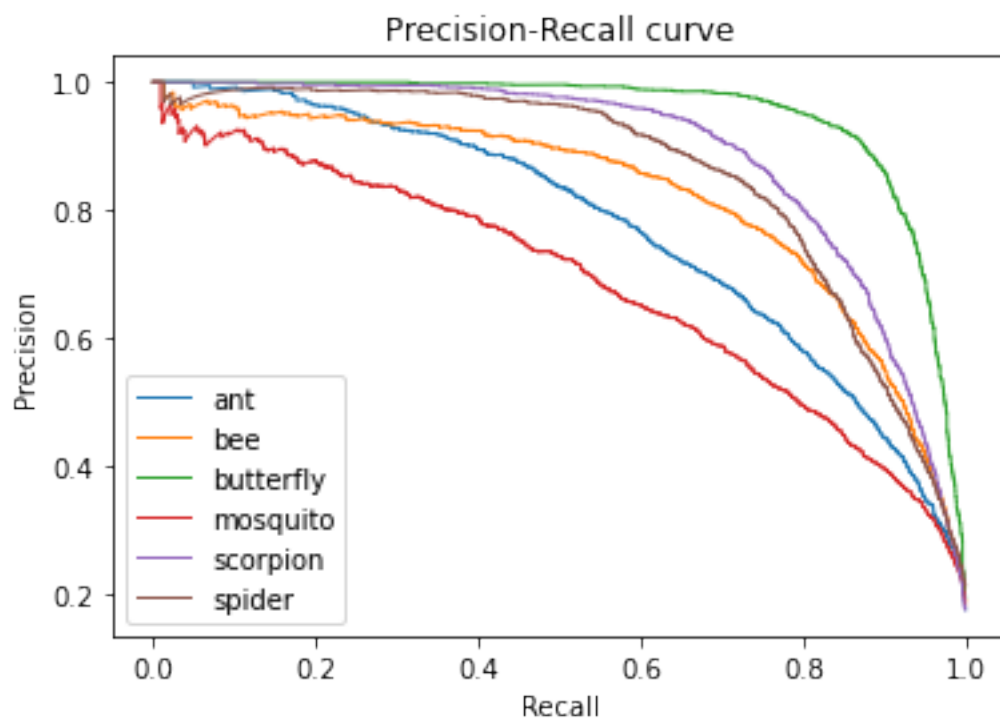
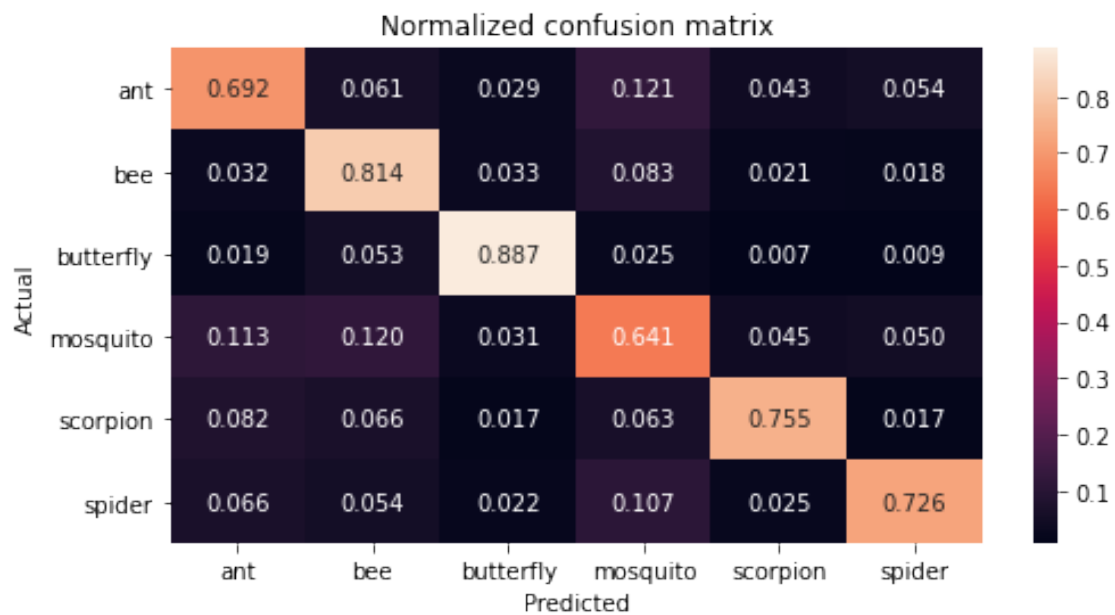


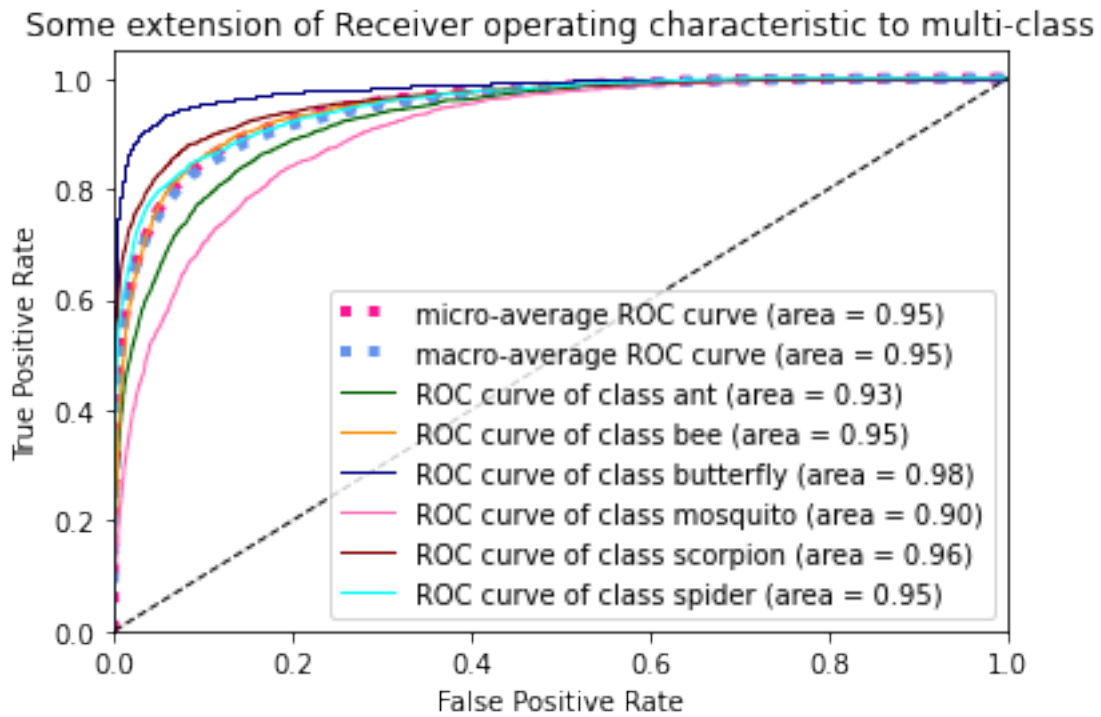
Test accuracy: 0.7527



Test loss: 0.709

	precision	recall	f1-score	support
ant	0.69	0.69	0.69	2478
bee	0.69	0.81	0.75	2488
butterfly	0.87	0.89	0.88	2557
mosquito	0.62	0.64	0.63	2527
scorpion	0.84	0.76	0.80	2468
spider	0.83	0.73	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:
0.945241 (macro),
0.945309 (weighted by prevalence)
One-vs-Rest ROC AUC scores:
0.945339 (macro),
0.945388 (weighted by prevalence)

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

Model: "Multi_Layer_Perceptron_relu_0.4D0_OL2"

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

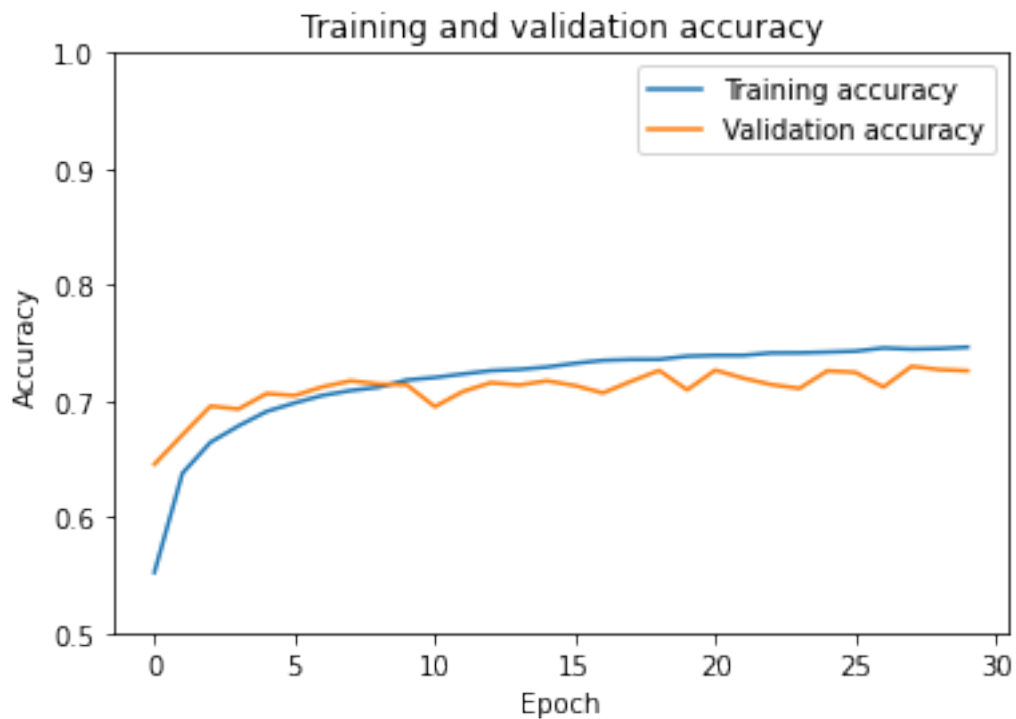
Dense1_relu (Dense)	(None, 32)	25120
BatchNormalization1 (BatchNo	(None, 32)	128
Dense2_relu (Dense)	(None, 32)	1056
Dropout_0.4 (Dropout)	(None, 32)	0
Dense3_relu (Dense)	(None, 32)	1056
Dense4_relu (Dense)	(None, 32)	1056
BatchNormalization2 (BatchNo	(None, 32)	128
Dense5_relu (Dense)	(None, 16)	528
Output (Dense)	(None, 6)	102

Total params: 29,174

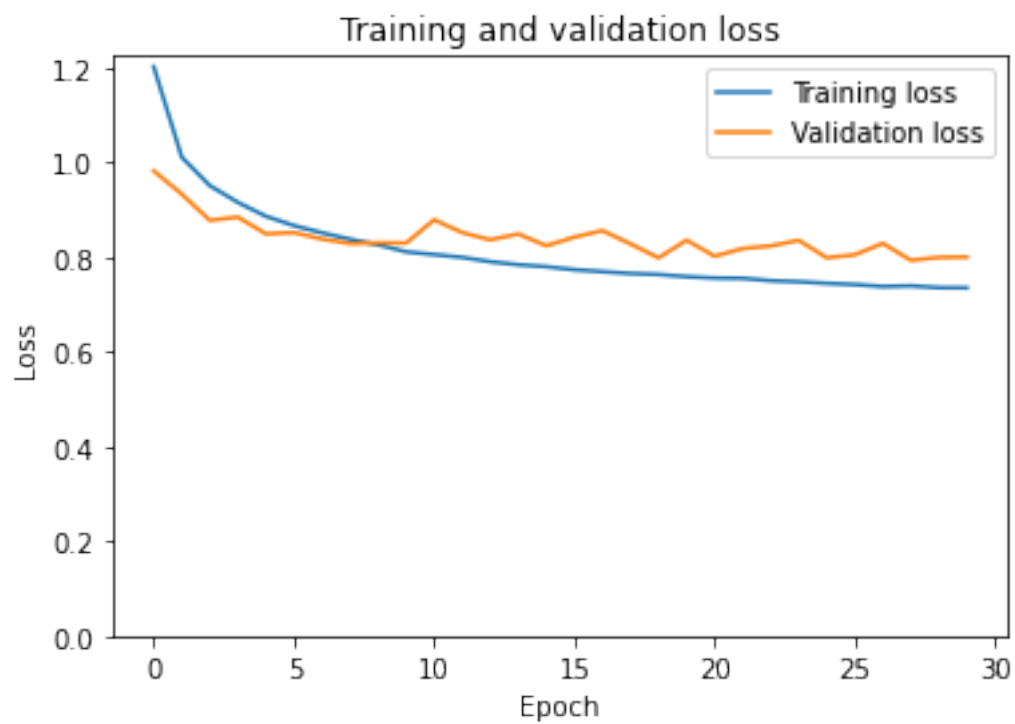
Trainable params: 29,046

Non-trainable params: 128

Total train time for 30 epochs = 67.684 seconds

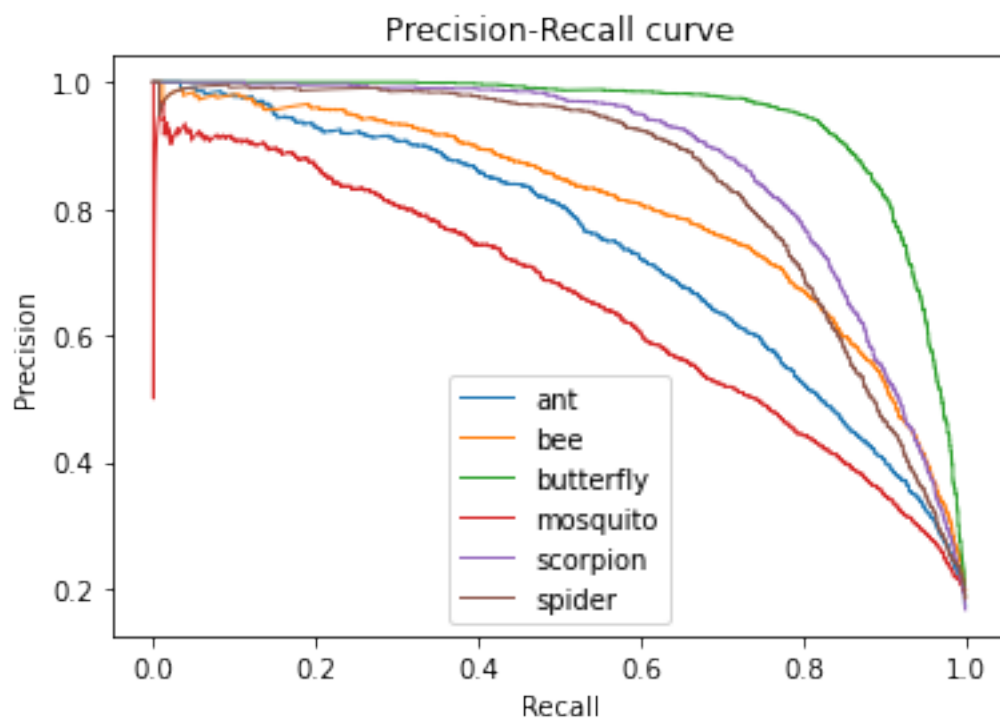
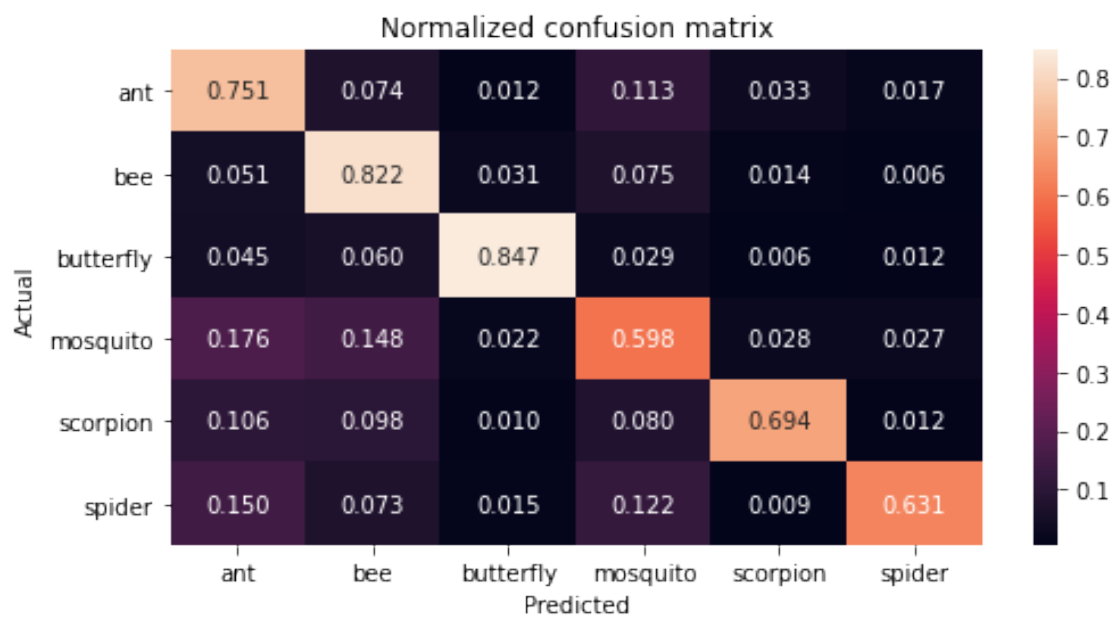


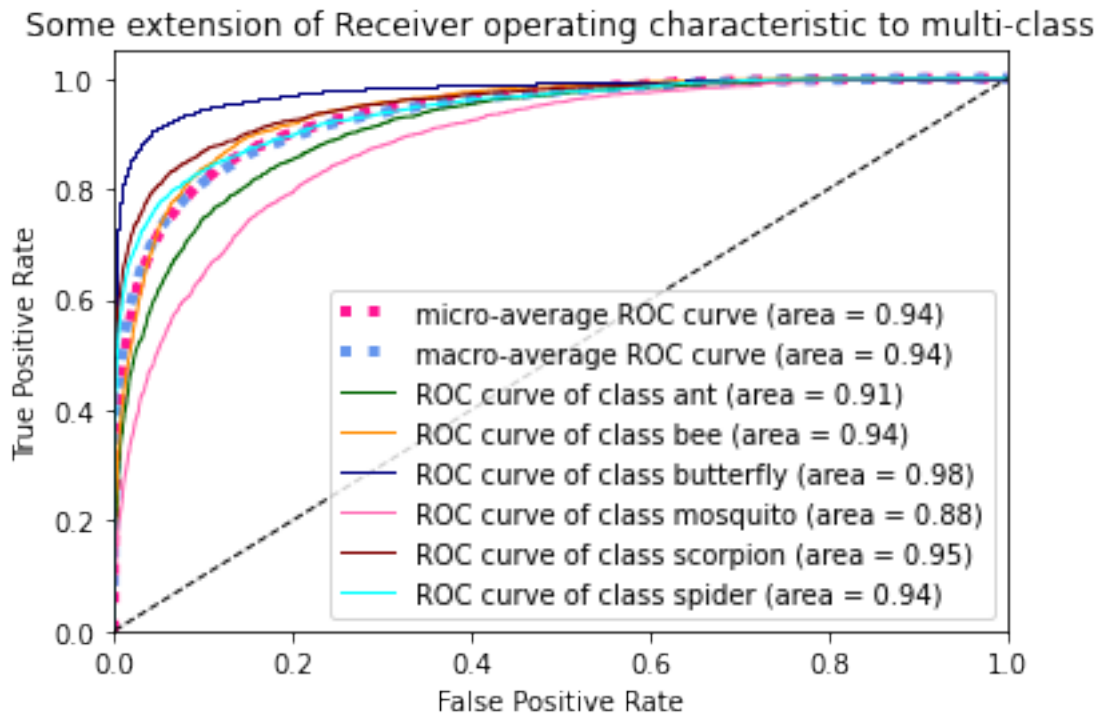
Test accuracy: 0.7245



Test loss: 0.8019

	precision	recall	f1-score	support
ant	0.58	0.75	0.66	2478
bee	0.64	0.82	0.72	2488
butterfly	0.91	0.85	0.88	2557
mosquito	0.59	0.60	0.60	2527
scorpion	0.88	0.69	0.78	2468
spider	0.89	0.63	0.74	2482
accuracy			0.72	15000
macro avg	0.75	0.72	0.73	15000
weighted avg	0.75	0.72	0.73	15000



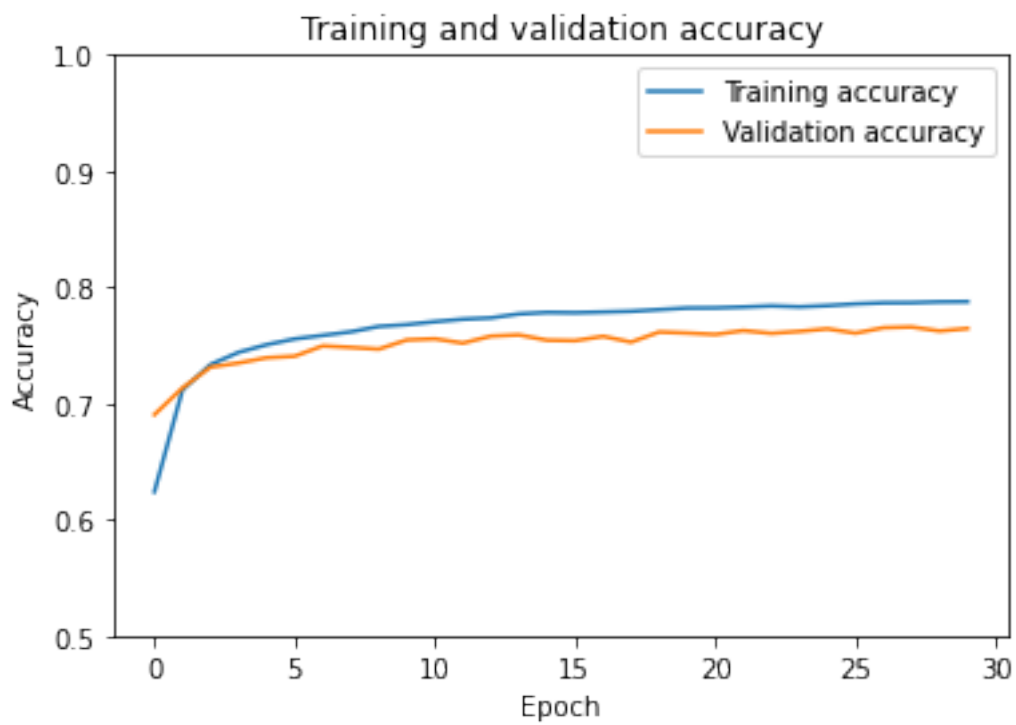


One-vs-One ROC AUC scores:
 0.934899 (macro),
 0.934966 (weighted by prevalence)
 One-vs-Rest ROC AUC scores:
 0.934990 (macro),
 0.935044 (weighted by prevalence)

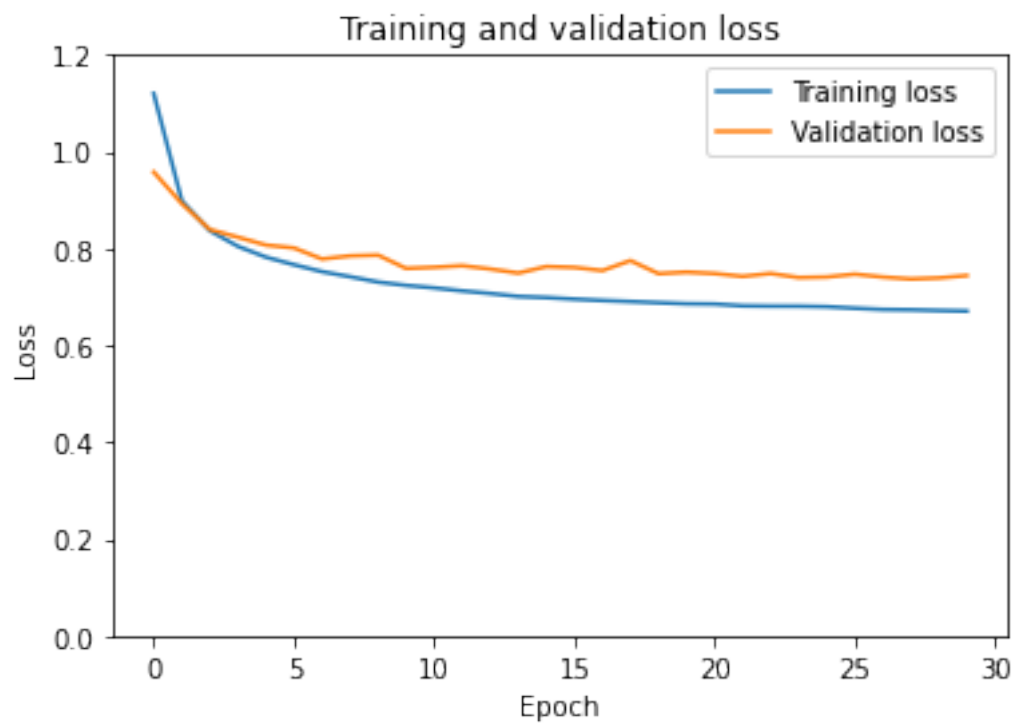
```
[ ]: model_0005L2, history_0005L2, score_0005L2, y_pred_0005L2 = run_model(l2_val=0.
    ↪0005)
```

Model: "Multi_Layer_Perceptron_relu_OD0_0.0005L2"

Layer (type)	Output Shape	Param #
Dense1_relu (Dense)	(None, 32)	25120
BatchNormalization1 (BatchNo	(None, 32)	128
Dense2_relu (Dense)	(None, 32)	1056
Dropout_0 (Dropout)	(None, 32)	0
Dense3_relu (Dense)	(None, 32)	1056
Dense4_relu (Dense)	(None, 32)	1056
BatchNormalization2 (BatchNo	(None, 32)	128
Dense5_relu (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 = 71.622 seconds		

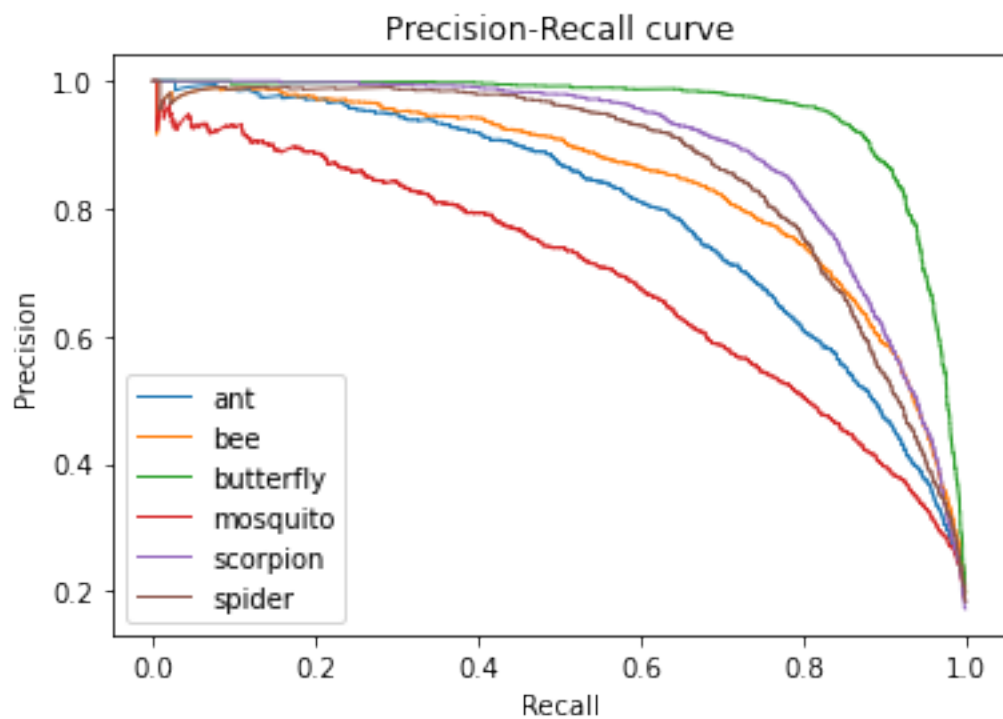
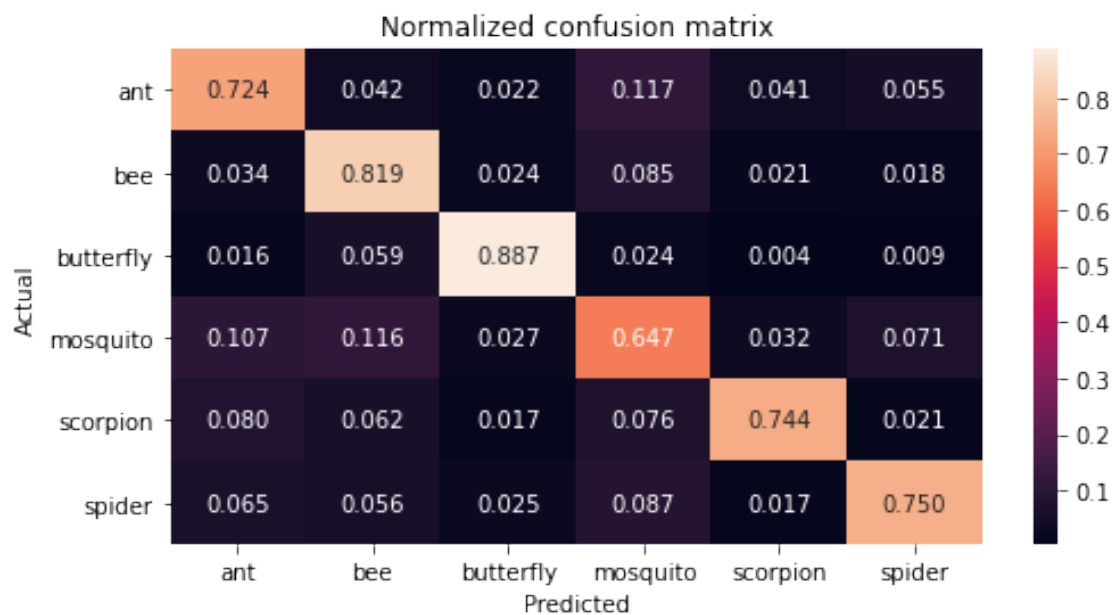


Test accuracy: 0.7618

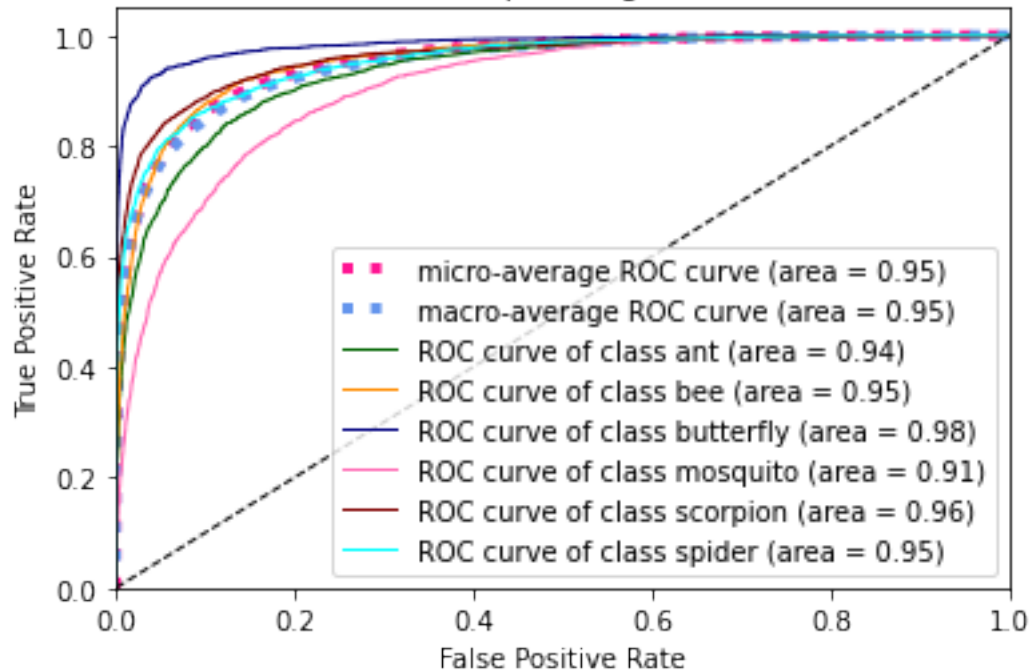


Test loss: 0.7508

	precision	recall	f1-score	support
ant	0.70	0.72	0.71	2478
bee	0.71	0.82	0.76	2488
butterfly	0.89	0.89	0.89	2557
mosquito	0.63	0.65	0.64	2527
scorpion	0.86	0.74	0.80	2468
spider	0.81	0.75	0.78	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:
 0.948583 (macro),
 0.948645 (weighted by prevalence)
 One-vs-Rest ROC AUC scores:
 0.948676 (macro),
 0.948715 (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_relu_0.1D0_0.0005L2"

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

Dense1_relu (Dense)	(None, 32)	25120

BatchNormalization1 (BatchNo	(None, 32)	128

Dense2_relu (Dense)	(None, 32)	1056

Dropout_0.1 (Dropout)	(None, 32)	0

Dense3_relu (Dense)	(None, 32)	1056

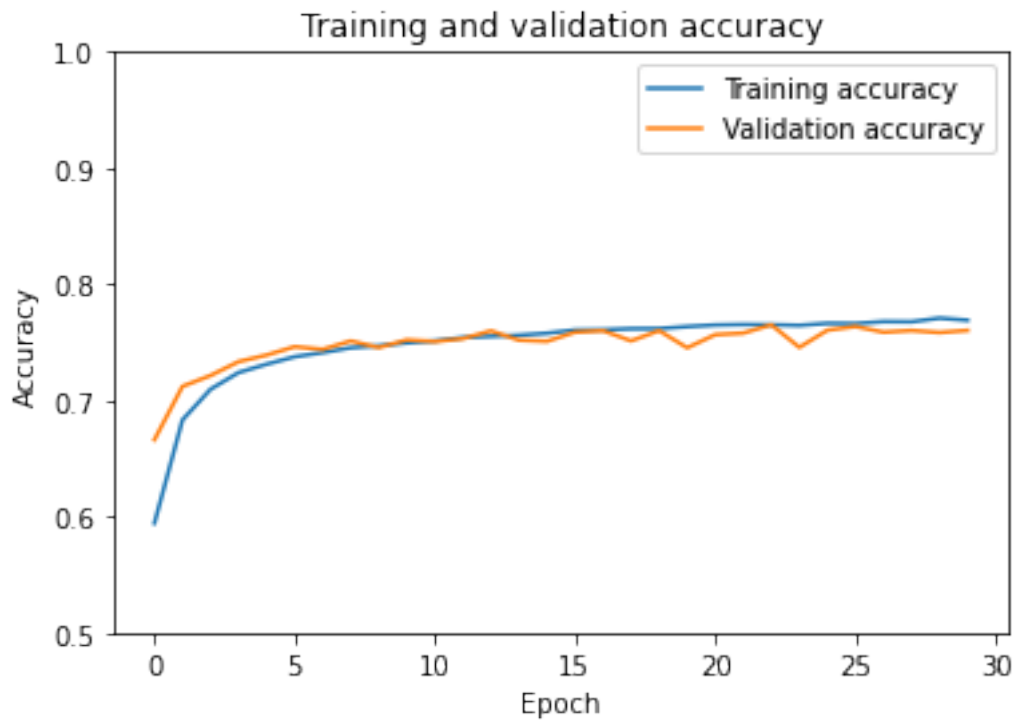
Dense4_relu (Dense)	(None, 32)	1056

BatchNormalization2 (BatchNo	(None, 32)	128

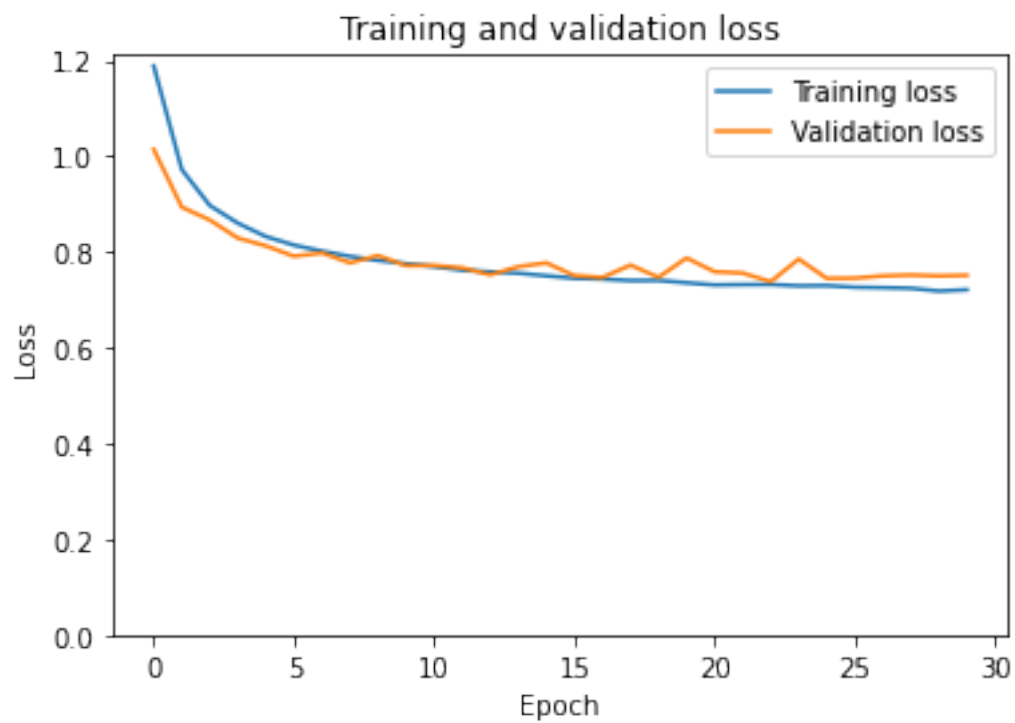
Dense5_relu (Dense)	(None, 16)	528

Output (Dense)	(None, 6)	102
=====		
Total params: 29,174		
Trainable params: 29,046		
Non-trainable params: 128		

Total train time for 30 epochs = 71.933 seconds		

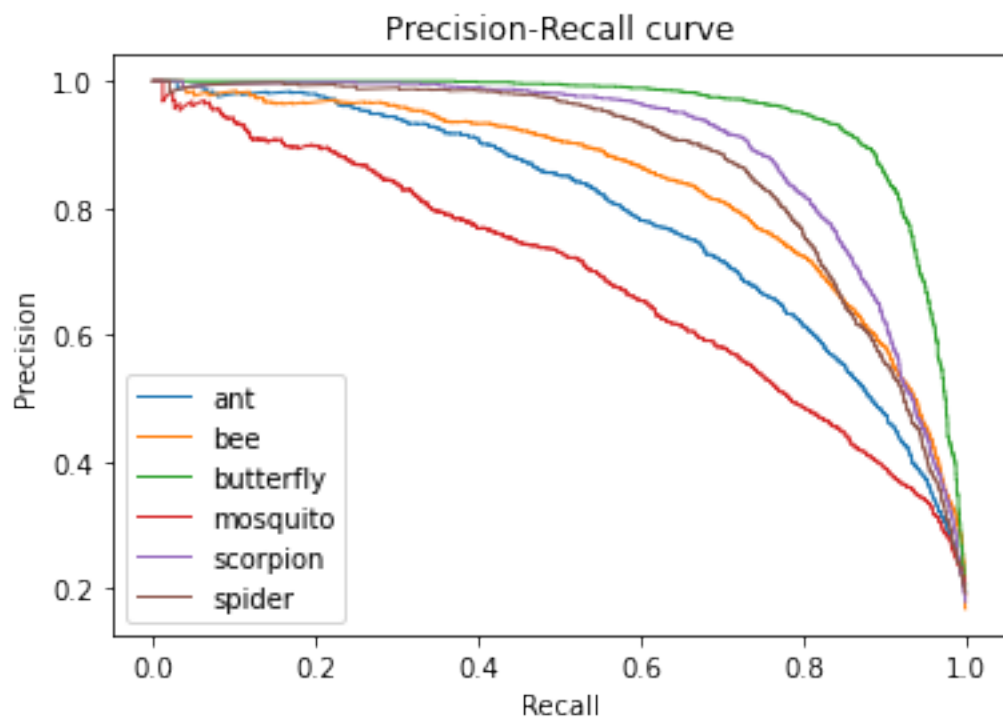
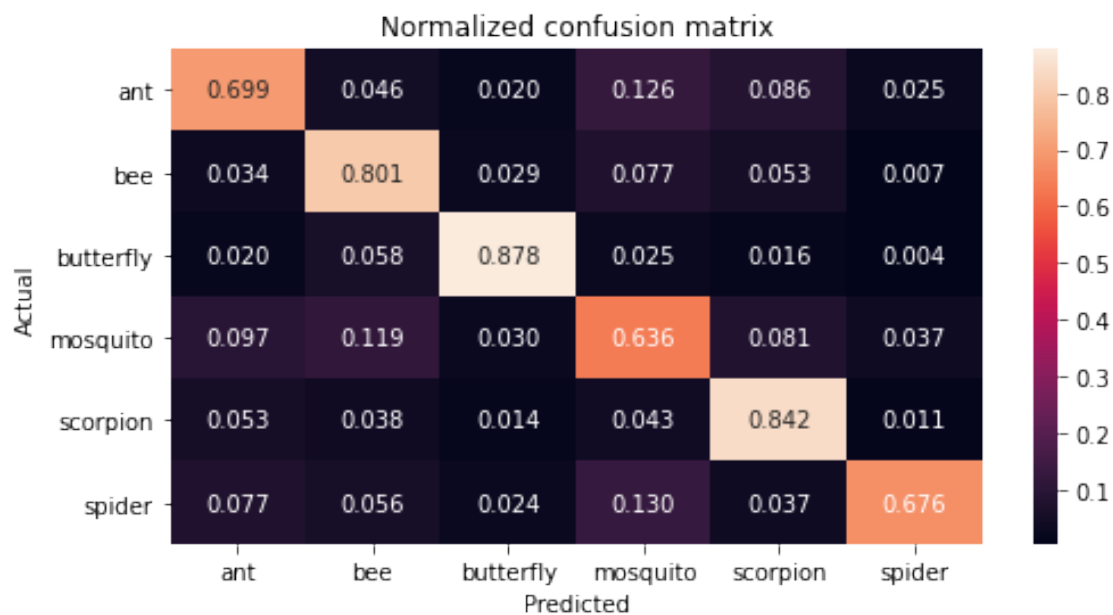


Test accuracy: 0.7553

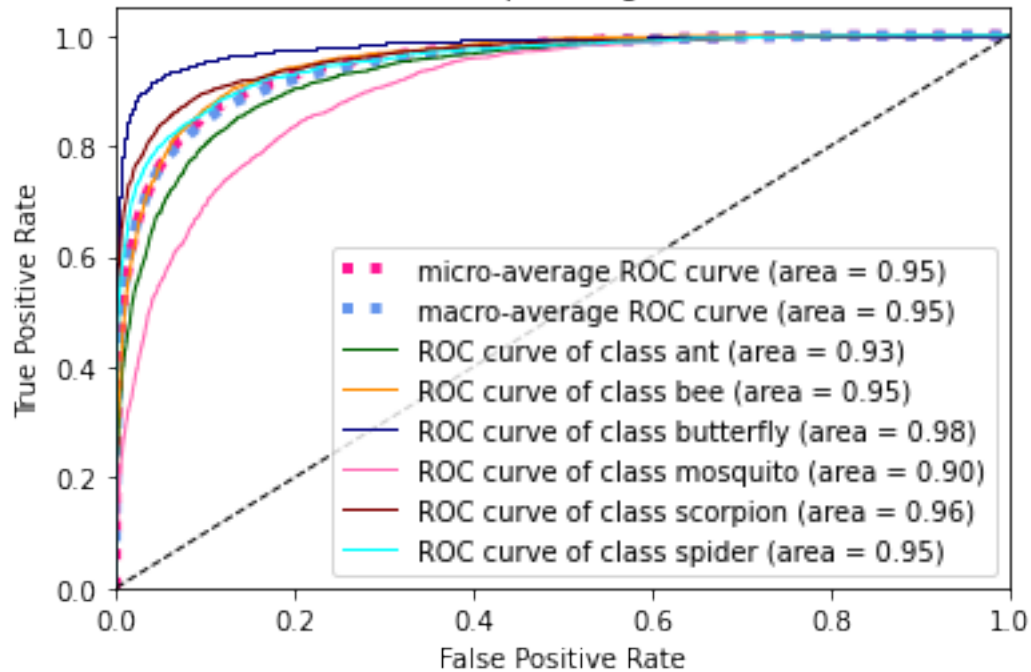


Test loss: 0.7567

	precision	recall	f1-score	support
ant	0.71	0.70	0.70	2478
bee	0.71	0.80	0.76	2488
butterfly	0.89	0.88	0.88	2557
mosquito	0.62	0.64	0.63	2527
scorpion	0.75	0.84	0.79	2468
spider	0.89	0.68	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:
 0.947786 (macro),
 0.947824 (weighted by prevalence)
 One-vs-Rest ROC AUC scores:
 0.947841 (macro),
 0.947868 (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_relu_0.2D0_0.0005L2"

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

Dense1_relu (Dense)	(None, 32)	25120

BatchNormalization1 (BatchNo	(None, 32)	128

Dense2_relu (Dense)	(None, 32)	1056

Dropout_0.2 (Dropout)	(None, 32)	0

Dense3_relu (Dense)	(None, 32)	1056

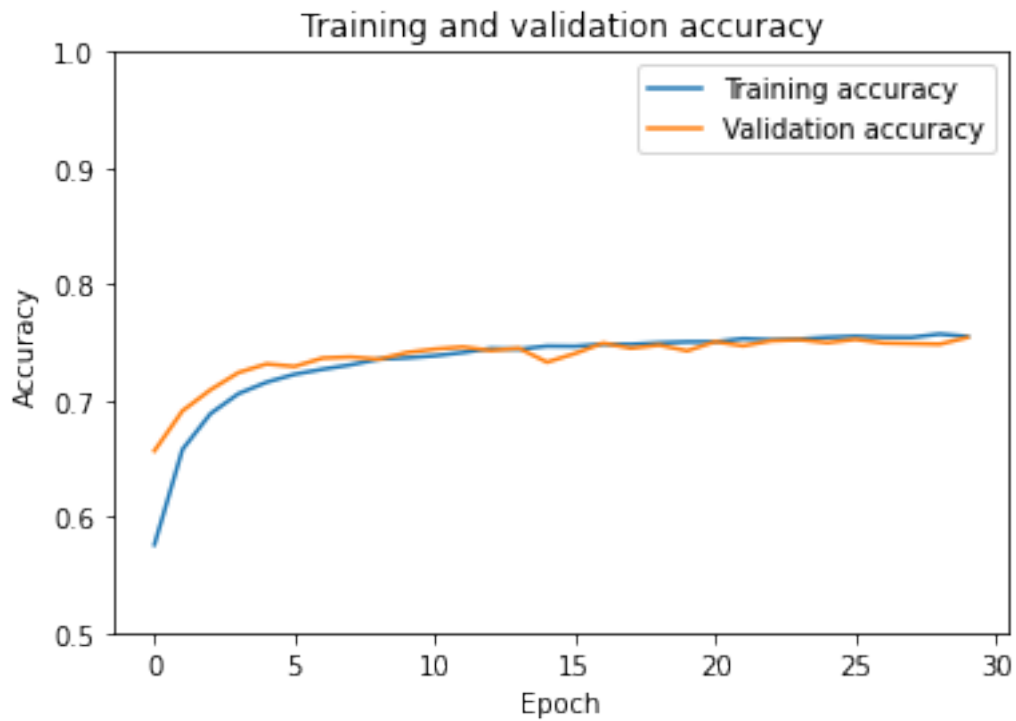
Dense4_relu (Dense)	(None, 32)	1056

BatchNormalization2 (BatchNo	(None, 32)	128

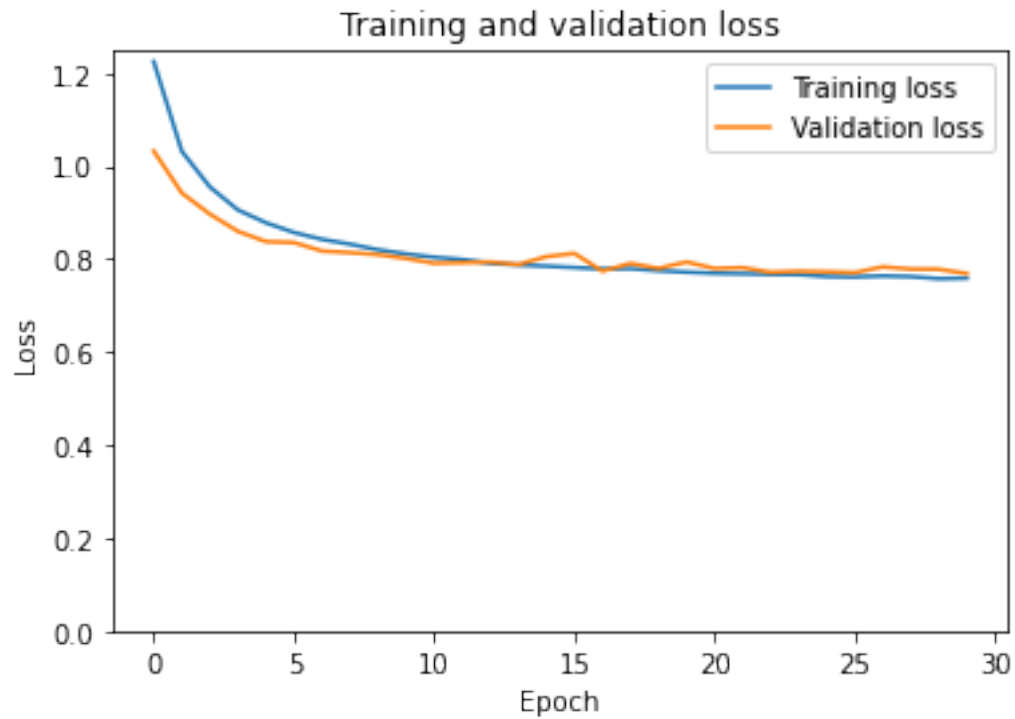
Dense5_relu (Dense)	(None, 16)	528

Output (Dense)	(None, 6)	102
=====		
Total params: 29,174		
Trainable params: 29,046		
Non-trainable params: 128		

Total train time for 30 epochs = 71.579 seconds		

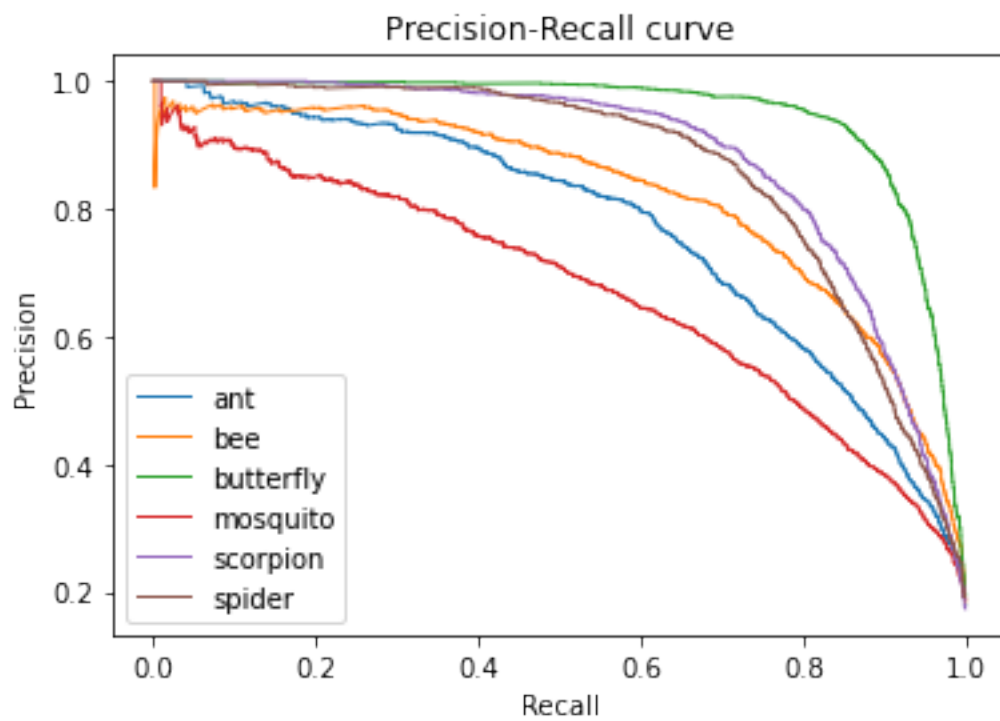
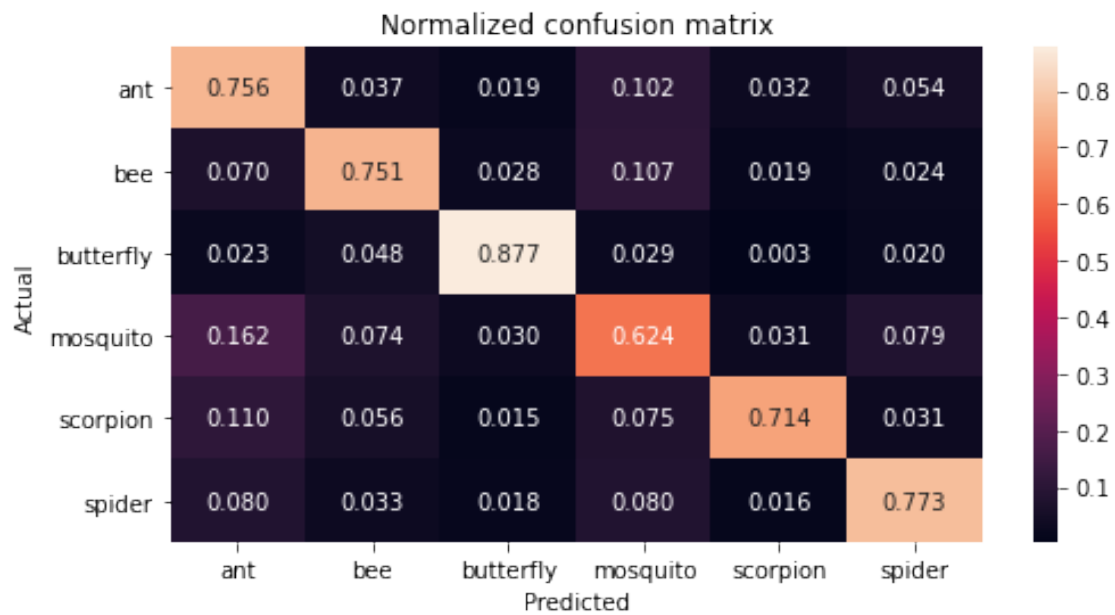


Test accuracy: 0.7495

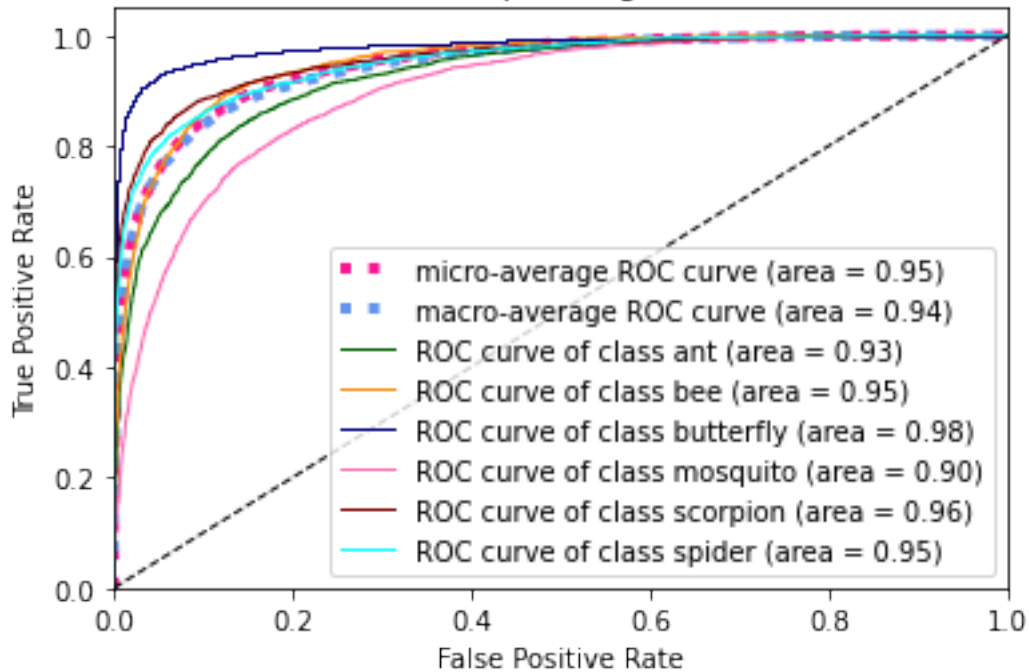


Test loss: 0.7769

	precision	recall	f1-score	support
ant	0.63	0.76	0.69	2478
bee	0.75	0.75	0.75	2488
butterfly	0.89	0.88	0.88	2557
mosquito	0.62	0.62	0.62	2527
scorpion	0.88	0.71	0.79	2468
spider	0.79	0.77	0.78	2482
accuracy			0.75	15000
macro avg	0.76	0.75	0.75	15000
weighted avg	0.76	0.75	0.75	15000



Some extension of Receiver operating characteristic to multi-class



One-vs-One ROC AUC scores:
 0.943922 (macro),
 0.943984 (weighted by prevalence)
 One-vs-Rest ROC AUC scores:
 0.944009 (macro),
 0.944055 (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_relu_0.4D0_0.0005L2"

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

Dense1_relu (Dense)	(None, 32)	25120

BatchNormalization1 (BatchNo	(None, 32)	128

Dense2_relu (Dense)	(None, 32)	1056

Dropout_0.4 (Dropout)	(None, 32)	0

Dense3_relu (Dense)	(None, 32)	1056

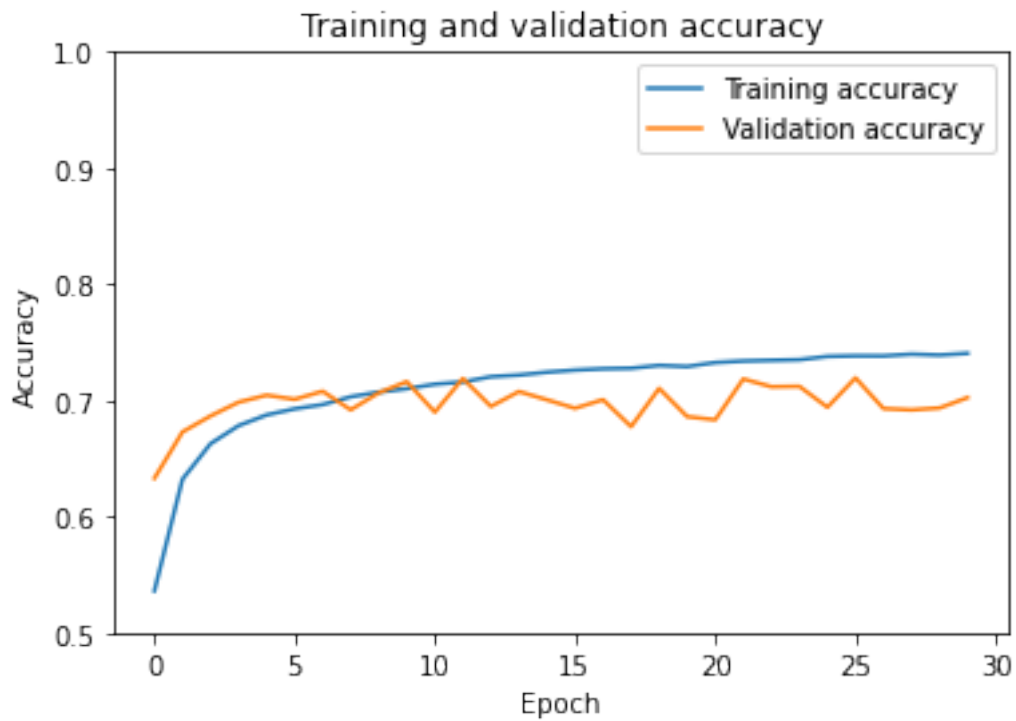
Dense4_relu (Dense)	(None, 32)	1056

BatchNormalization2 (BatchNo	(None, 32)	128

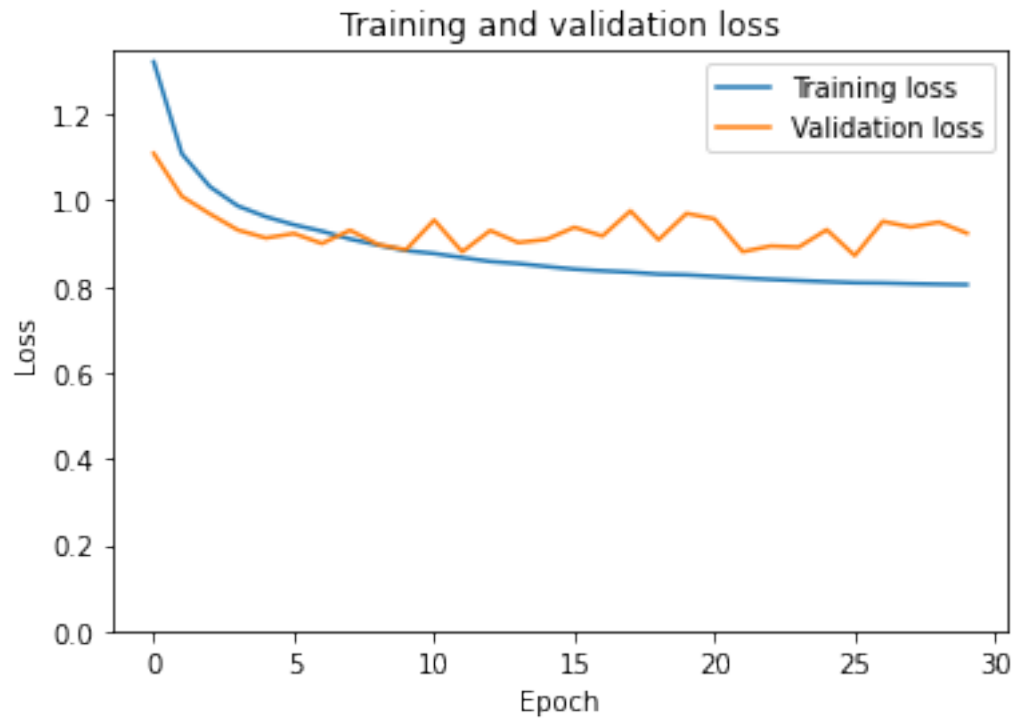
Dense5_relu (Dense)	(None, 16)	528

Output (Dense)	(None, 6)	102
=====		
Total params: 29,174		
Trainable params: 29,046		
Non-trainable params: 128		

Total train time for 30 epochs = 71.995 seconds		

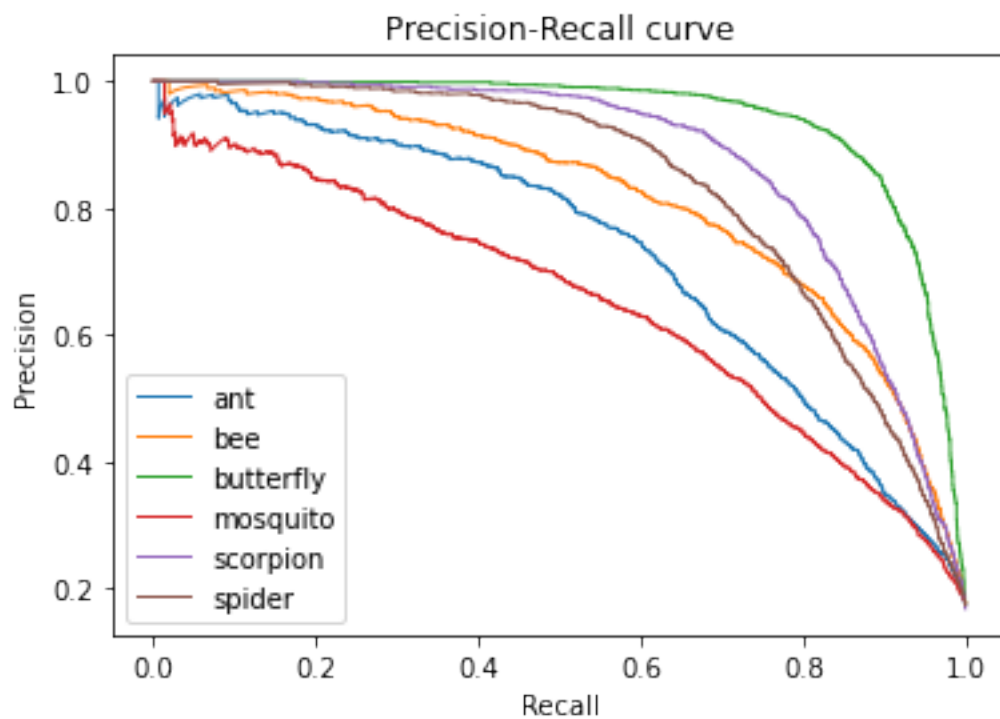
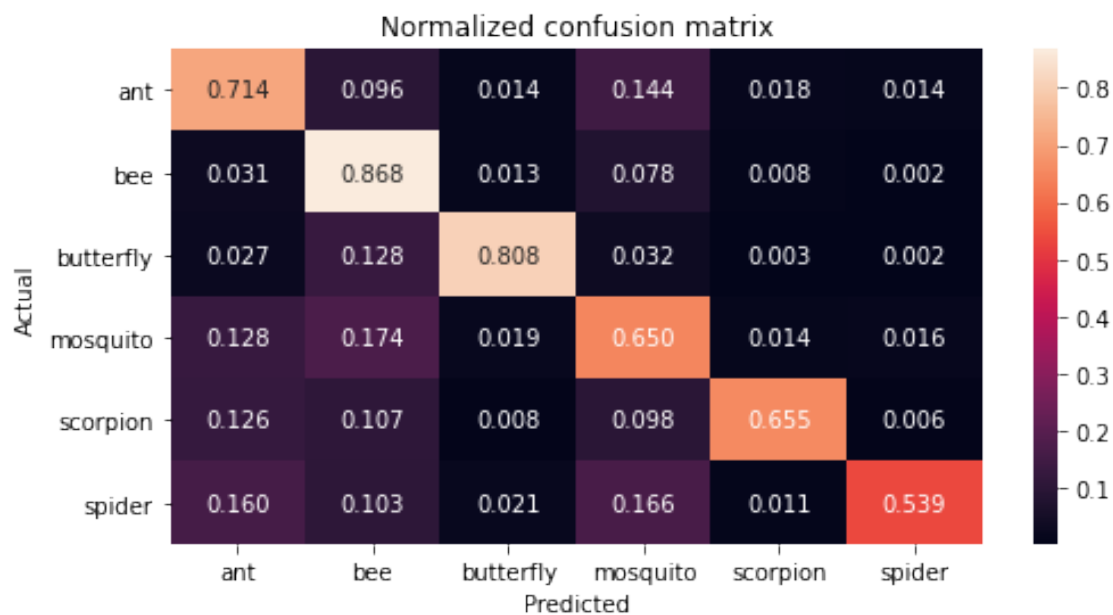


Test accuracy: 0.706

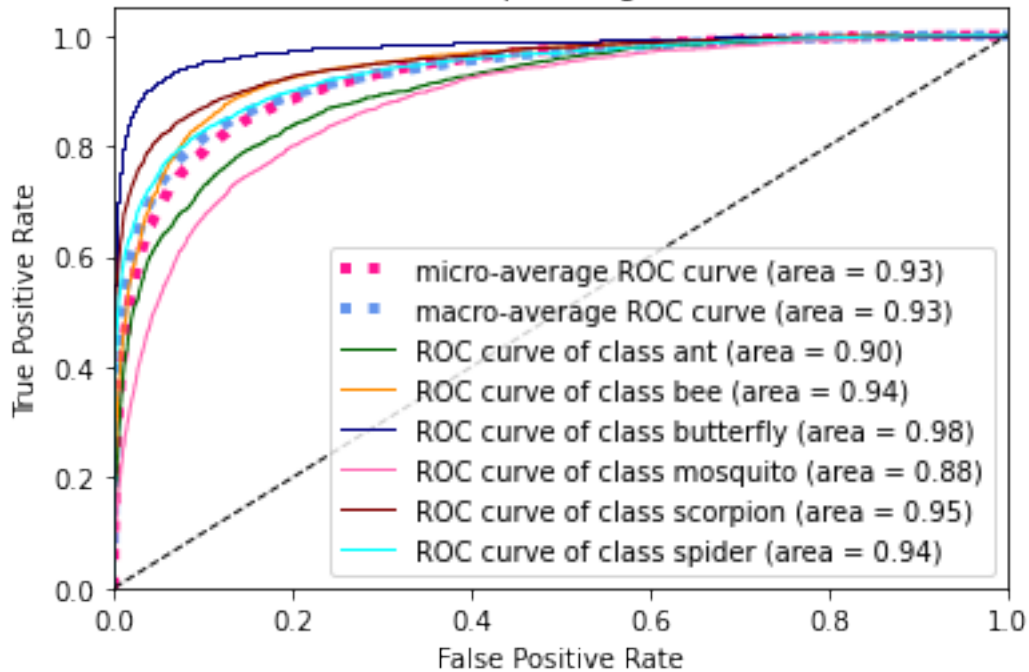


Test loss: 0.9156

	precision	recall	f1-score	support
ant	0.60	0.71	0.65	2478
bee	0.59	0.87	0.70	2488
butterfly	0.92	0.81	0.86	2557
mosquito	0.56	0.65	0.60	2527
scorpion	0.92	0.66	0.77	2468
spider	0.93	0.54	0.68	2482
accuracy			0.71	15000
macro avg	0.75	0.71	0.71	15000
weighted avg	0.75	0.71	0.71	15000



Some extension of Receiver operating characteristic to multi-class



One-vs-One ROC AUC scores:
 0.931804 (macro),
 0.931897 (weighted by prevalence)
 One-vs-Rest ROC AUC scores:
 0.931929 (macro),
 0.932005 (weighted by prevalence)

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

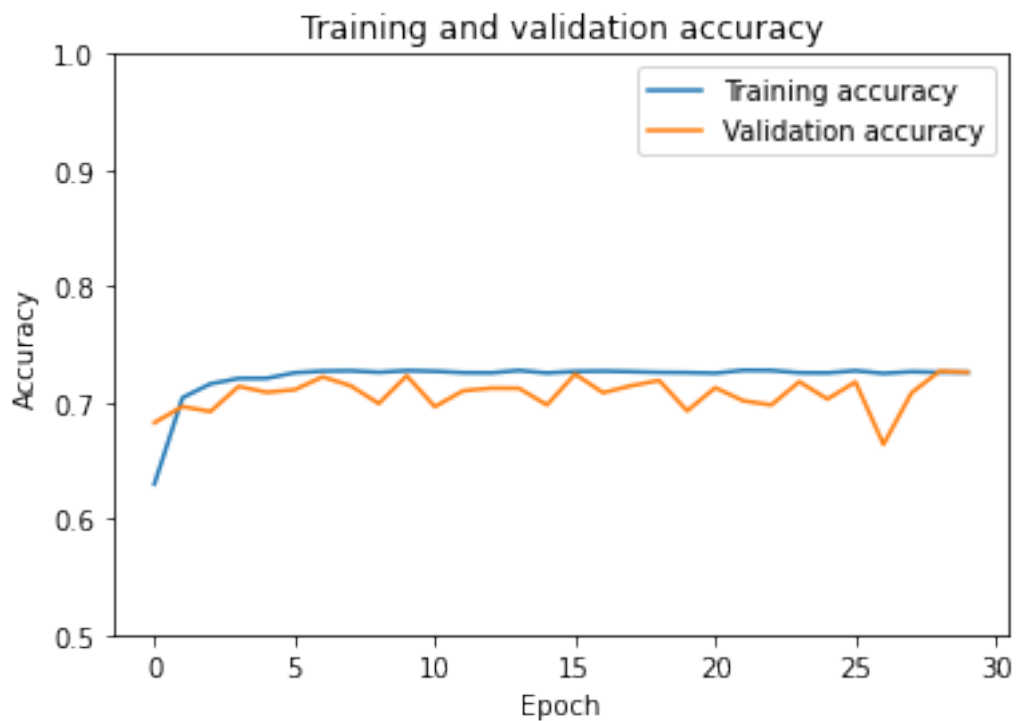
Model: "Multi_Layer_Perceptron_relu_OD0_0.01L2"

Layer (type)	Output Shape	Param #
Dense1_relu (Dense)	(None, 32)	25120

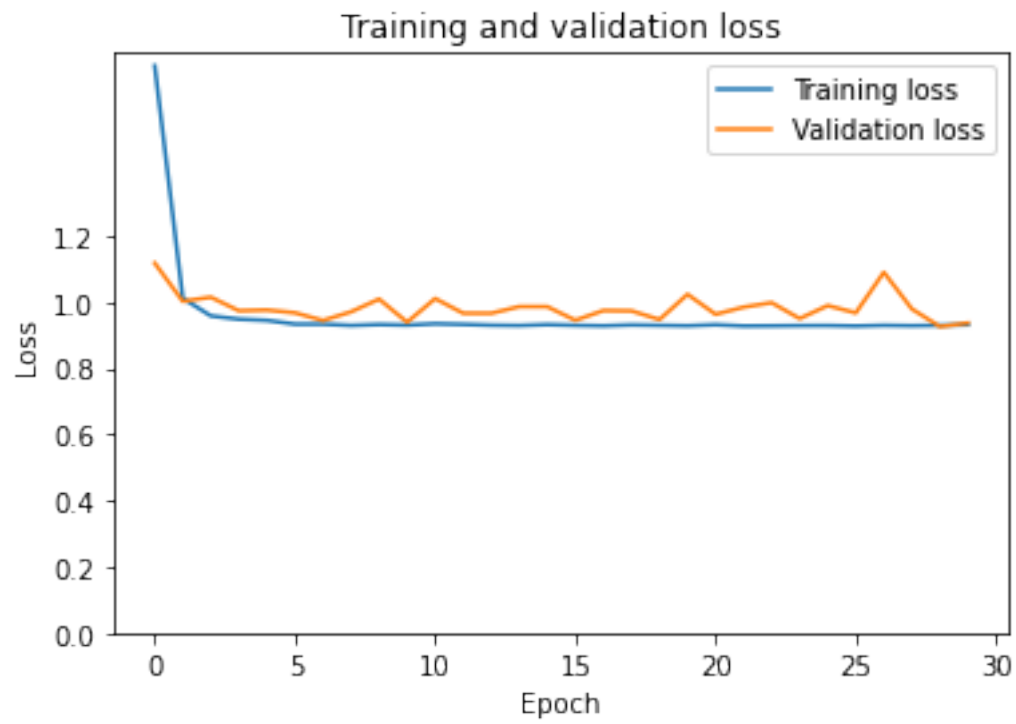
BatchNormalization1	(BatchNo (None, 32))	128
Dense2_relu	(Dense) (None, 32)	1056
Dropout_0	(Dropout) (None, 32)	0
Dense3_relu	(Dense) (None, 32)	1056
Dense4_relu	(Dense) (None, 32)	1056
BatchNormalization2	(BatchNo (None, 32))	128
Dense5_relu	(Dense) (None, 16)	528
Output	(Dense) (None, 6)	102

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

Total train time for 30 epochs = 71.368 seconds

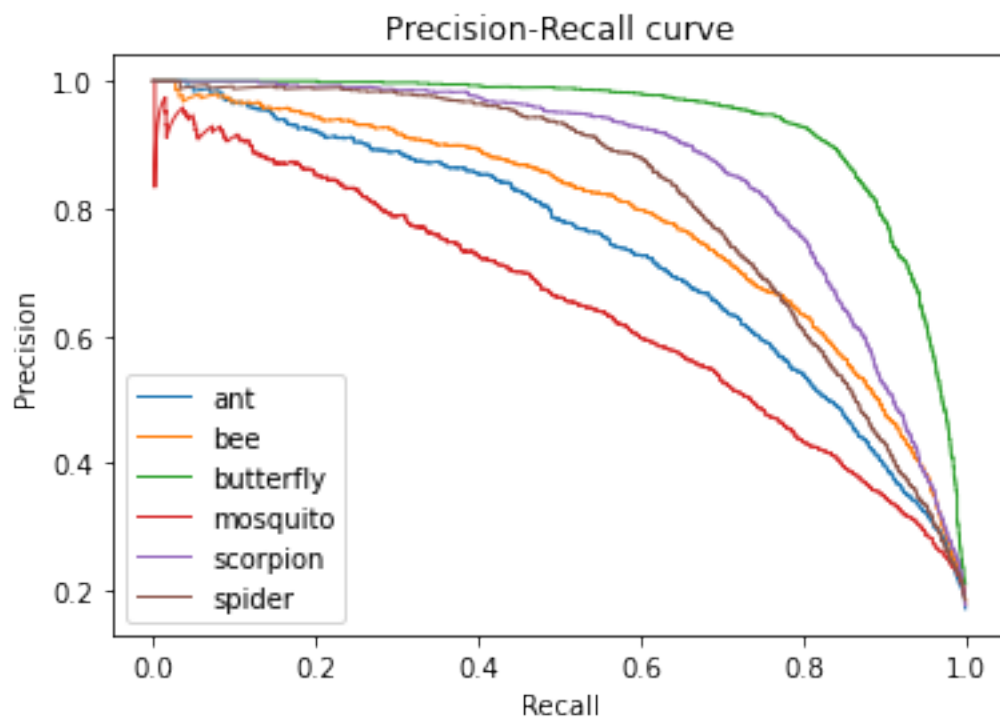
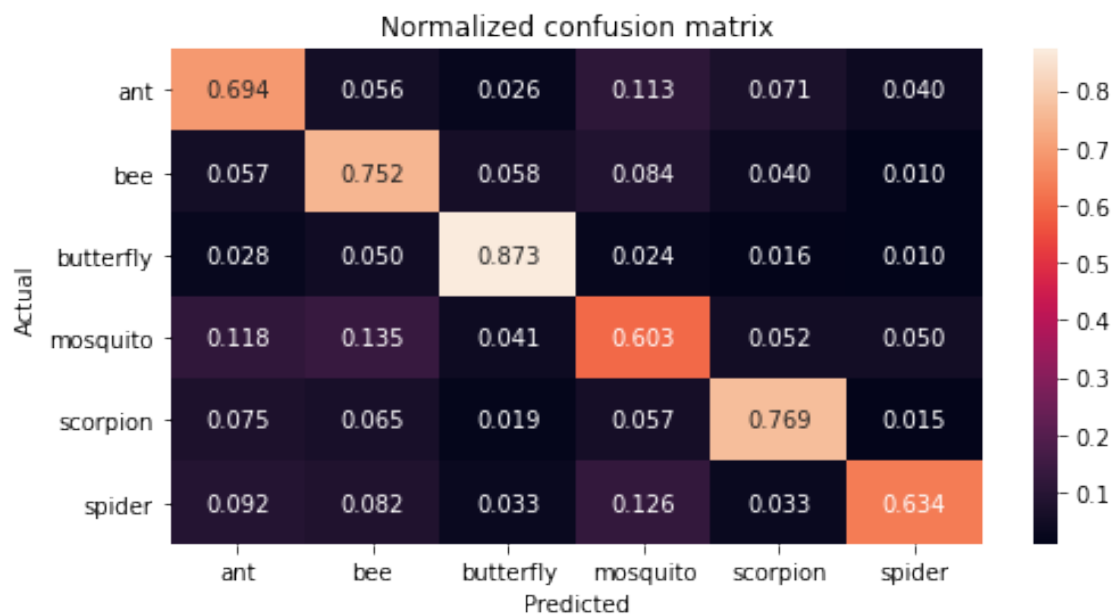


Test accuracy: 0.7211

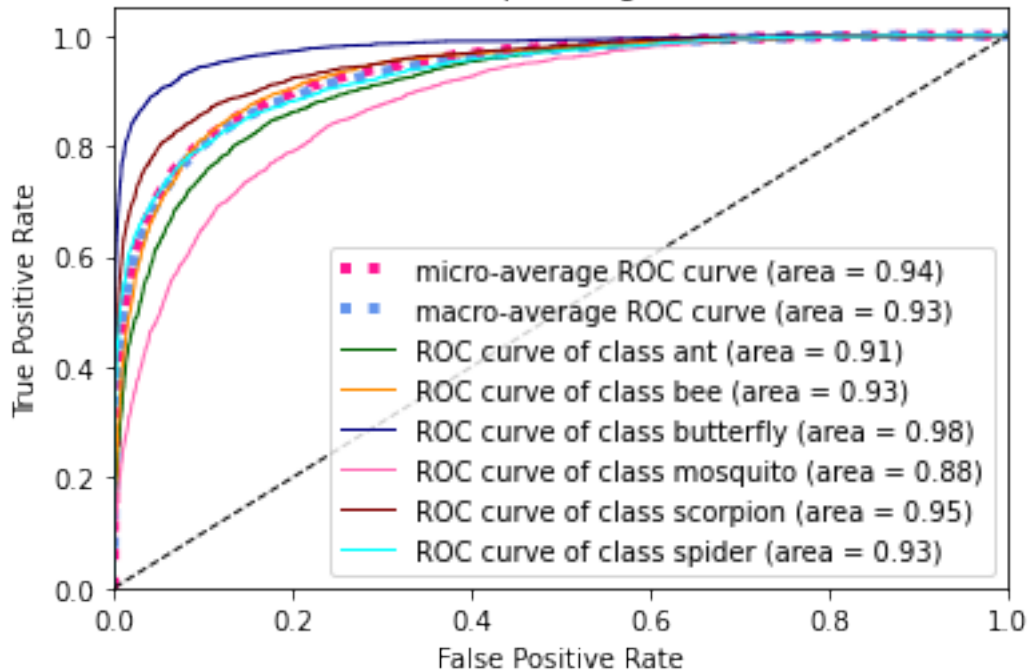


Test loss: 0.9464

	precision	recall	f1-score	support
ant	0.65	0.69	0.67	2478
bee	0.66	0.75	0.70	2488
butterfly	0.83	0.87	0.85	2557
mosquito	0.60	0.60	0.60	2527
scorpion	0.78	0.77	0.78	2468
spider	0.84	0.63	0.72	2482
accuracy			0.72	15000
macro avg	0.73	0.72	0.72	15000
weighted avg	0.73	0.72	0.72	15000



Some extension of Receiver operating characteristic to multi-class



One-vs-One ROC AUC scores:
0.931122 (macro),
0.931203 (weighted by prevalence)
One-vs-Rest ROC AUC scores:
0.931225 (macro),
0.931300 (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_relu_0.1D0_0.01L2"

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

Dense1_relu (Dense)	(None, 32)	25120

BatchNormalization1 (BatchNo	(None, 32)	128

Dense2_relu (Dense)	(None, 32)	1056

Dropout_0.1 (Dropout)	(None, 32)	0

Dense3_relu (Dense)	(None, 32)	1056

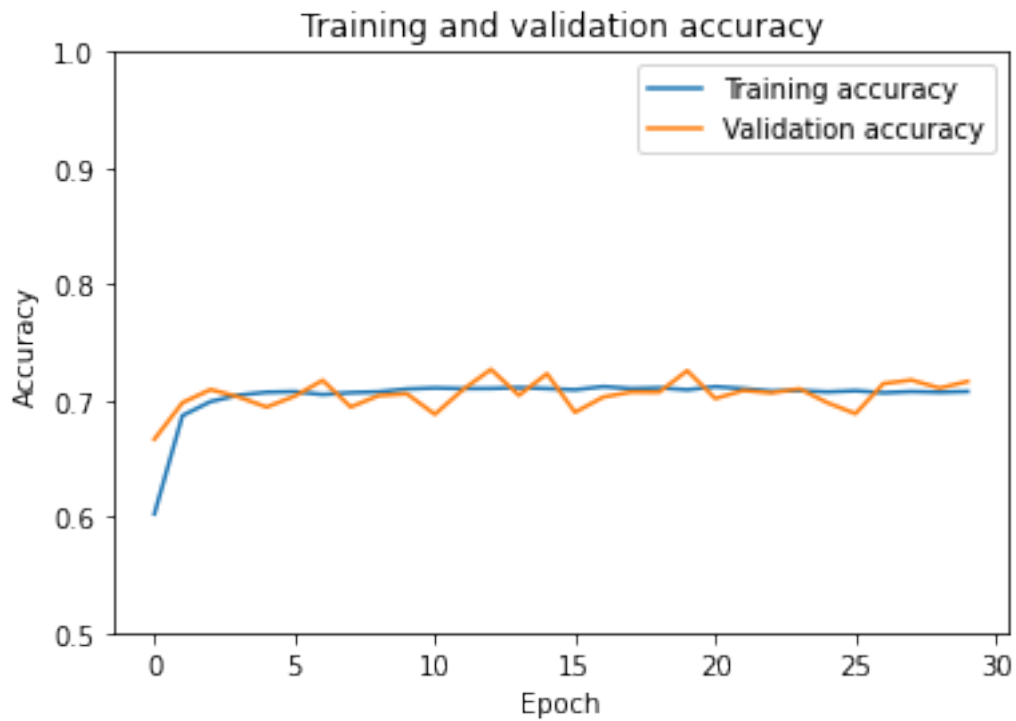
Dense4_relu (Dense)	(None, 32)	1056

BatchNormalization2 (BatchNo	(None, 32)	128

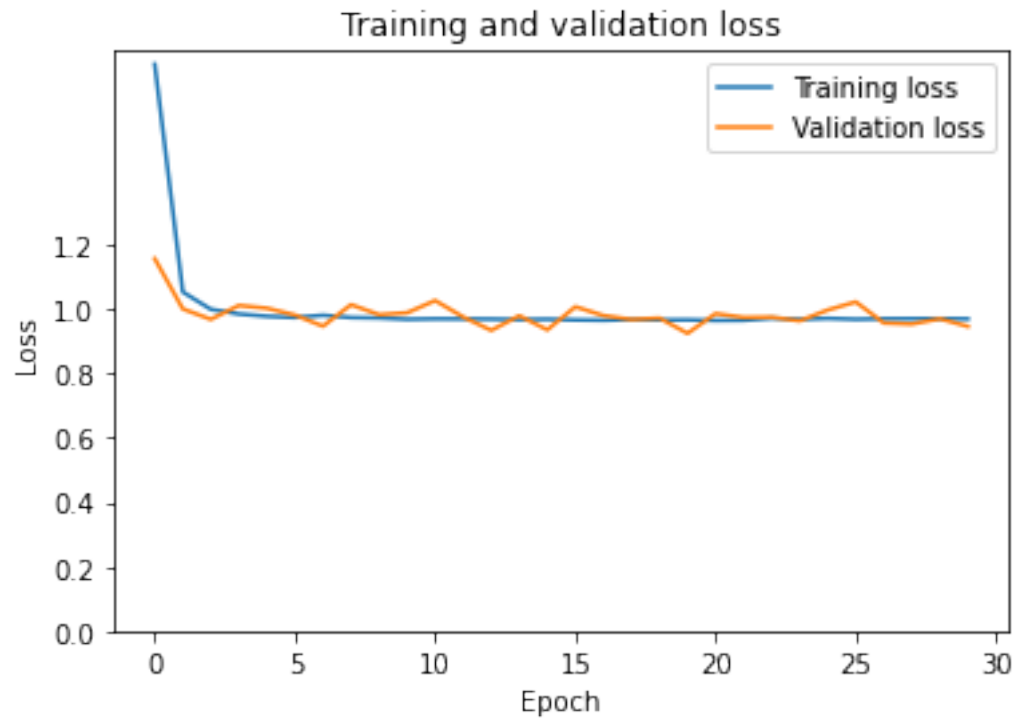
Dense5_relu (Dense)	(None, 16)	528

Output (Dense)	(None, 6)	102
=====		
Total params: 29,174		
Trainable params: 29,046		
Non-trainable params: 128		

Total train time for 30 epochs = 71.366 seconds		

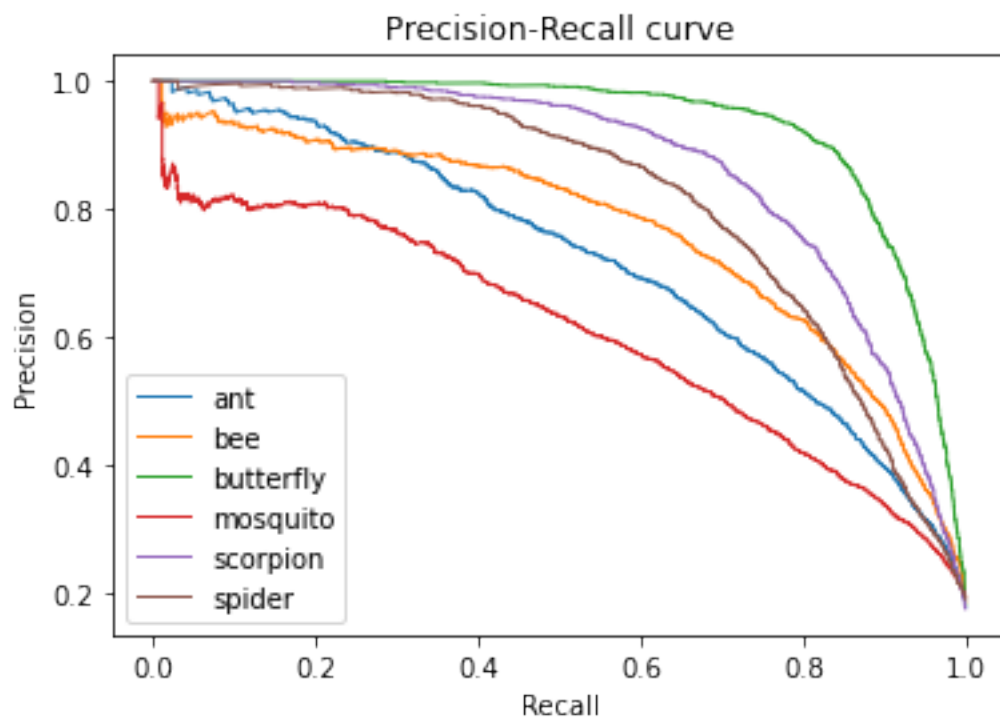
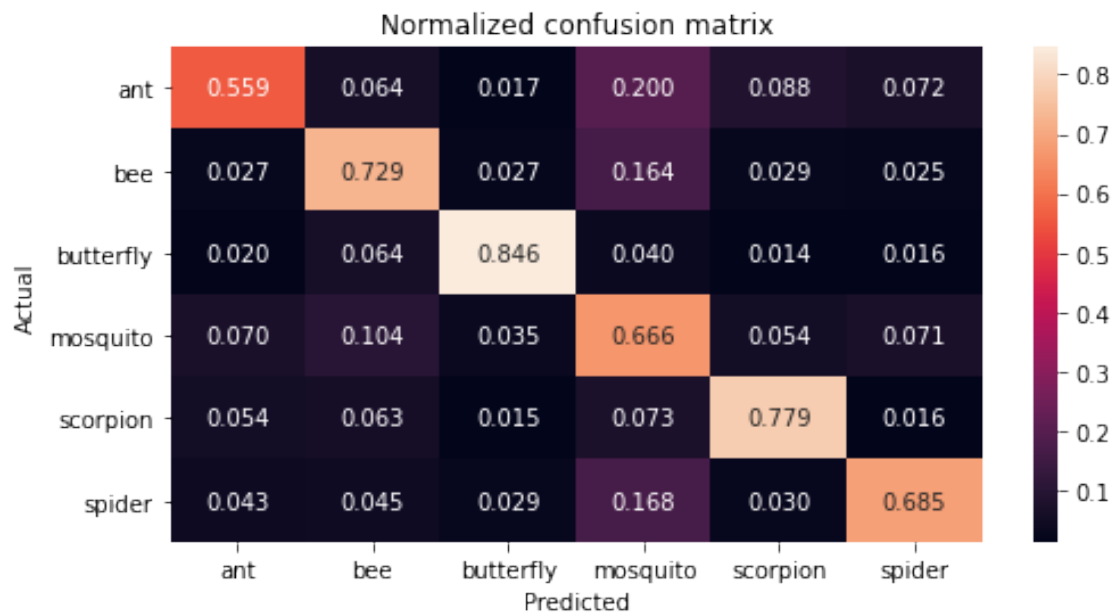


Test accuracy: 0.7111

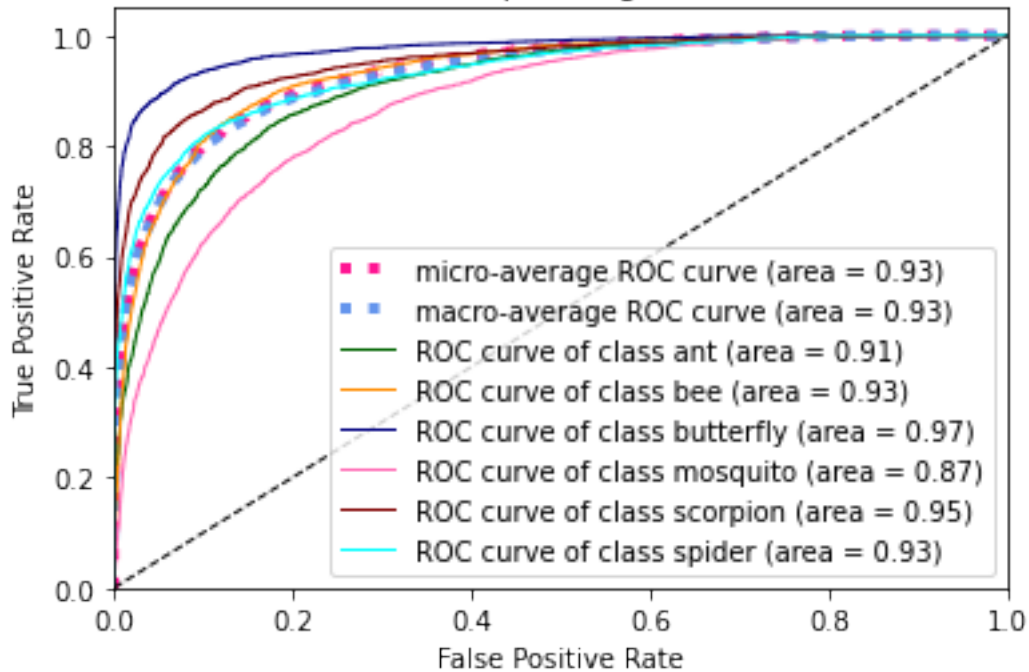


Test loss: 0.9581

	precision	recall	f1-score	support
ant	0.72	0.56	0.63	2478
bee	0.68	0.73	0.70	2488
butterfly	0.88	0.85	0.86	2557
mosquito	0.51	0.67	0.58	2527
scorpion	0.78	0.78	0.78	2468
spider	0.77	0.68	0.73	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:
 0.928403 (macro),
 0.928467 (weighted by prevalence)
 One-vs-Rest ROC AUC scores:
 0.928488 (macro),
 0.928543 (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_relu_0.2D0_0.01L2"

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

Dense1_relu (Dense)	(None, 32)	25120

BatchNormalization1 (BatchNo	(None, 32)	128

Dense2_relu (Dense)	(None, 32)	1056

Dropout_0.2 (Dropout)	(None, 32)	0

Dense3_relu (Dense)	(None, 32)	1056

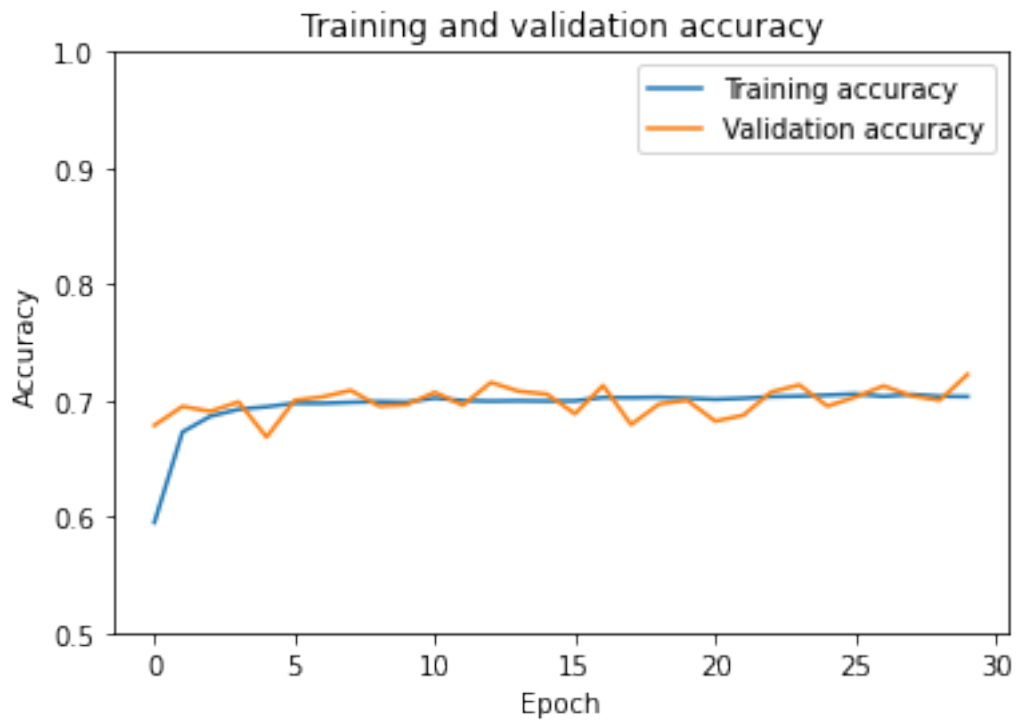
Dense4_relu (Dense)	(None, 32)	1056

BatchNormalization2 (BatchNo	(None, 32)	128

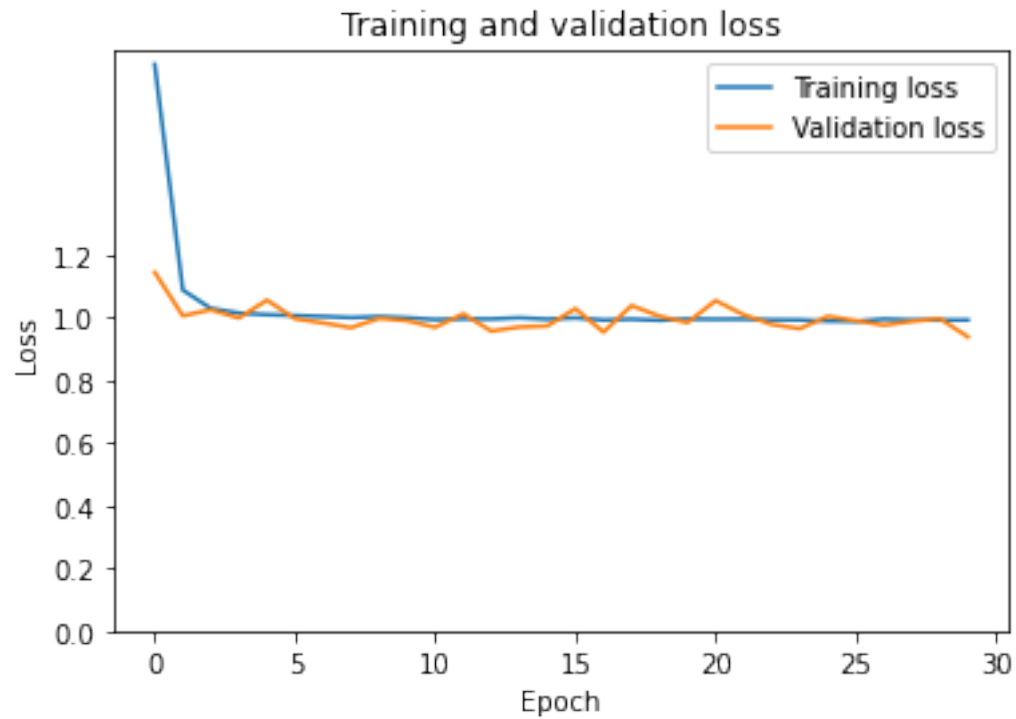
Dense5_relu (Dense)	(None, 16)	528

Output (Dense)	(None, 6)	102
=====		
Total params: 29,174		
Trainable params: 29,046		
Non-trainable params: 128		

Total train time for 30 epochs = 70.964 seconds		

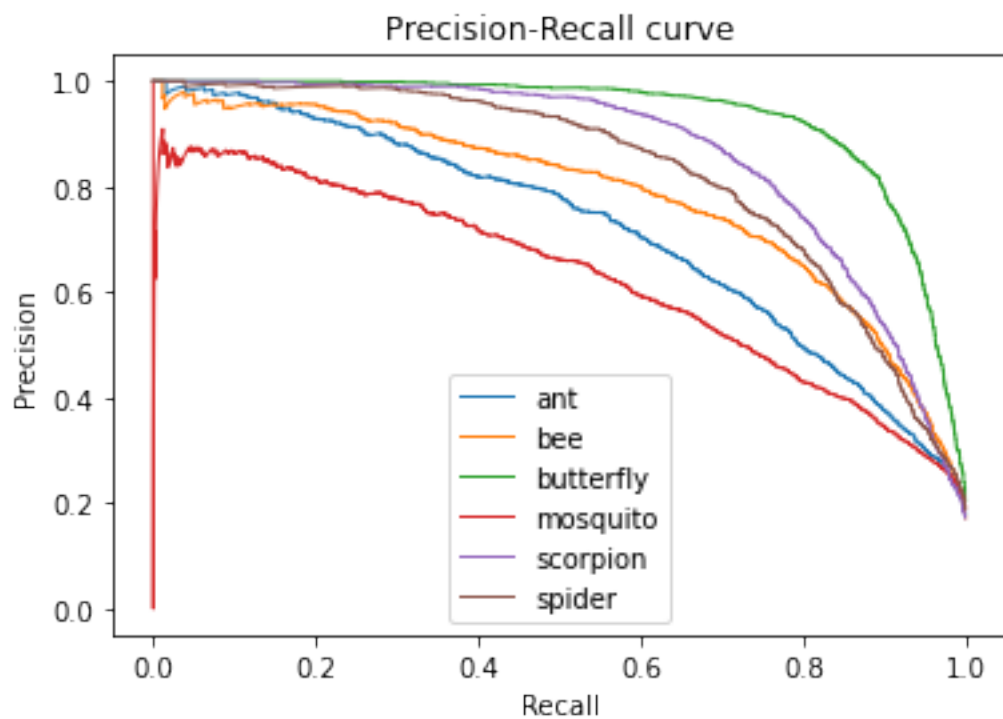
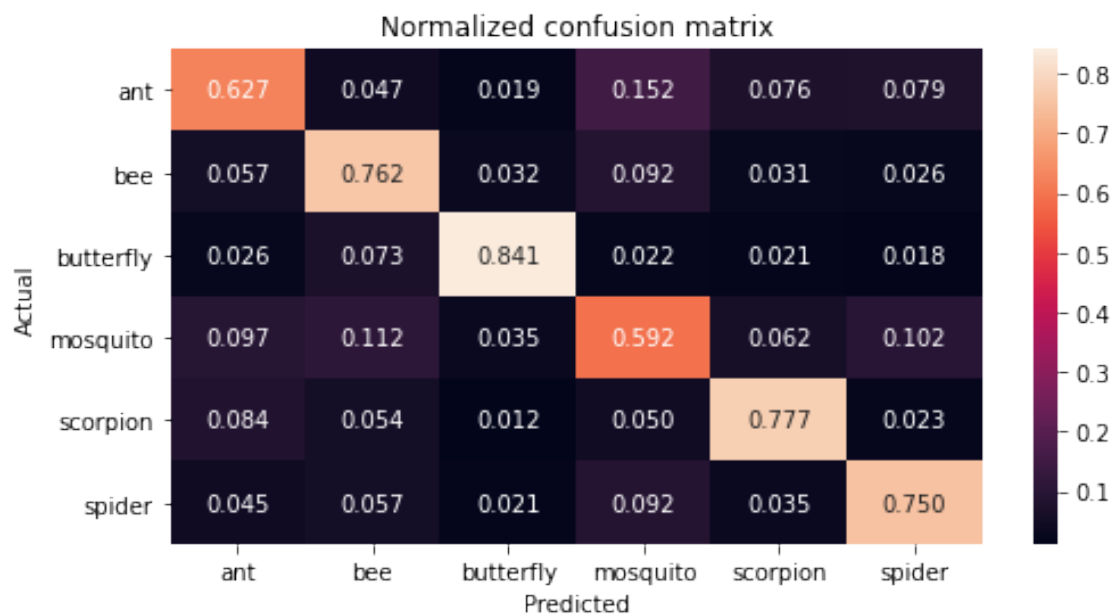


Test accuracy: 0.7249

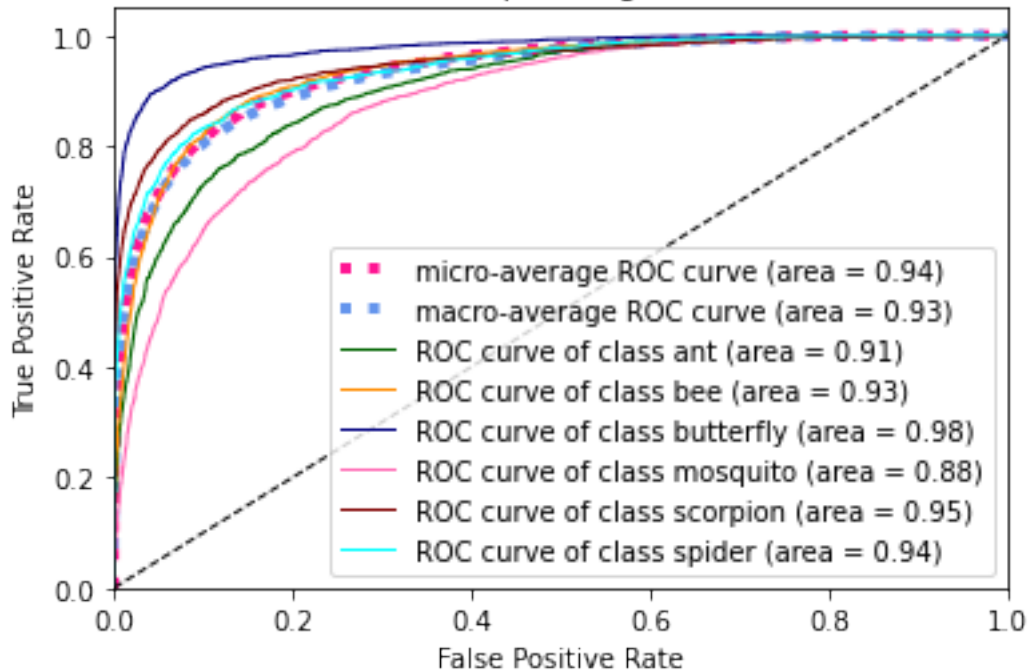


Test loss: 0.9387

	precision	recall	f1-score	support
ant	0.67	0.63	0.65	2478
bee	0.69	0.76	0.72	2488
butterfly	0.88	0.84	0.86	2557
mosquito	0.60	0.59	0.59	2527
scorpion	0.77	0.78	0.78	2468
spider	0.75	0.75	0.75	2482
accuracy			0.72	15000
macro avg	0.73	0.72	0.72	15000
weighted avg	0.73	0.72	0.72	15000



Some extension of Receiver operating characteristic to multi-class



One-vs-One ROC AUC scores:
 0.930630 (macro),
 0.930700 (weighted by prevalence)
 One-vs-Rest ROC AUC scores:
 0.930711 (macro),
 0.930785 (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_relu_0.4D0_0.01L2"

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

Dense1_relu (Dense)	(None, 32)	25120

BatchNormalization1 (BatchNo	(None, 32)	128

Dense2_relu (Dense)	(None, 32)	1056

Dropout_0.4 (Dropout)	(None, 32)	0

Dense3_relu (Dense)	(None, 32)	1056

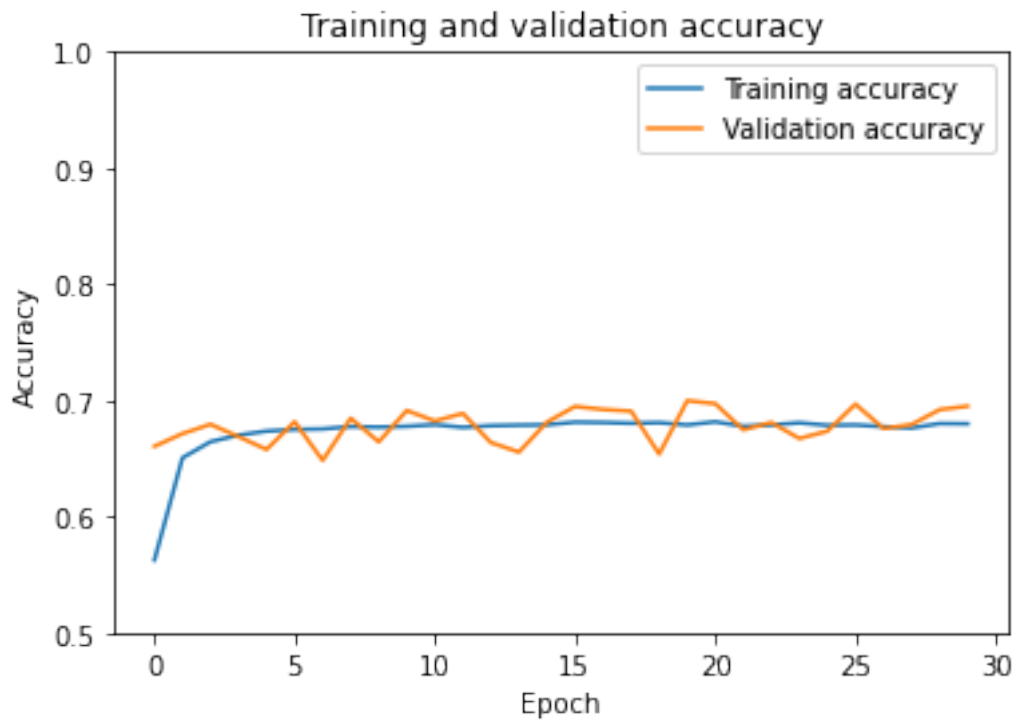
Dense4_relu (Dense)	(None, 32)	1056

BatchNormalization2 (BatchNo	(None, 32)	128

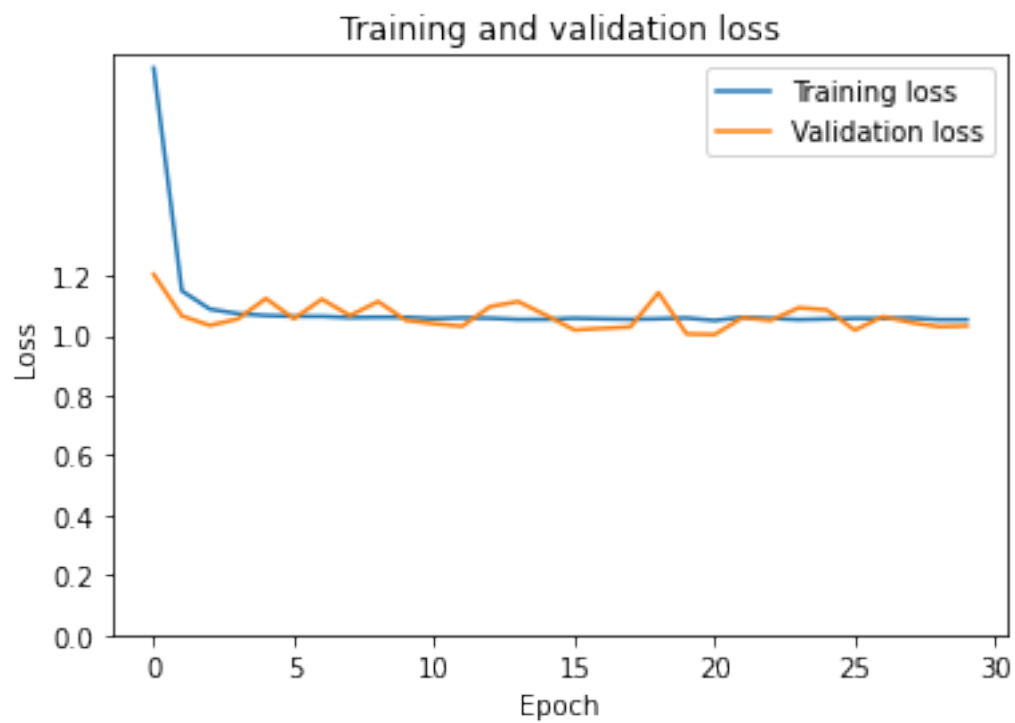
Dense5_relu (Dense)	(None, 16)	528

Output (Dense)	(None, 6)	102
=====		
Total params: 29,174		
Trainable params: 29,046		
Non-trainable params: 128		

Total train time for 30 epochs = 72.090 seconds		

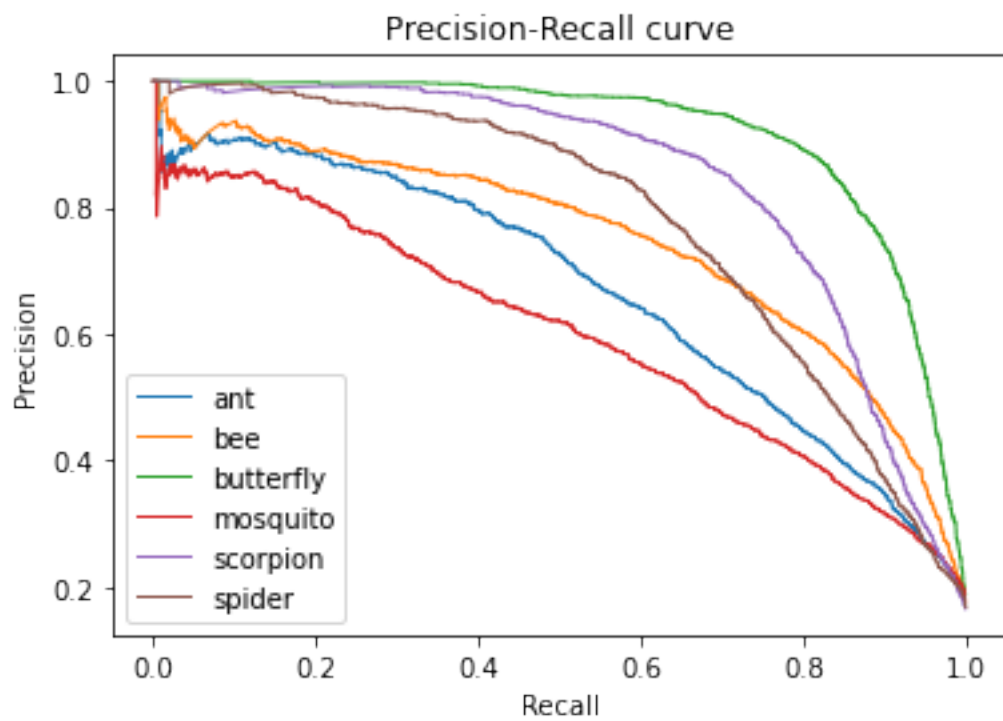
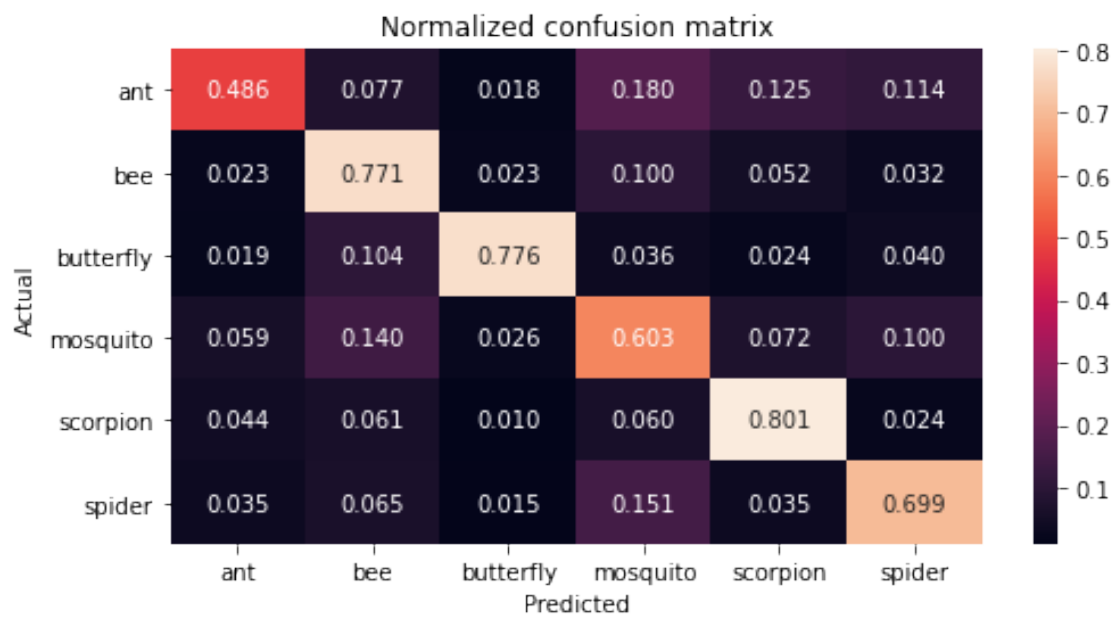


Test accuracy: 0.6897

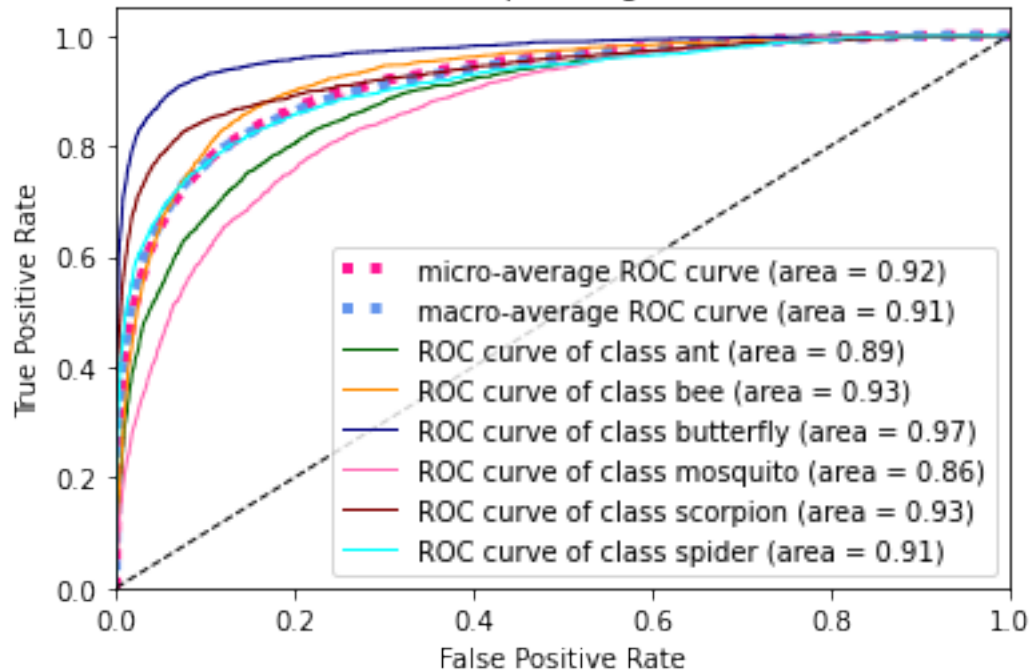


Test loss: 1.039

	precision	recall	f1-score	support
ant	0.73	0.49	0.58	2478
bee	0.63	0.77	0.69	2488
butterfly	0.90	0.78	0.83	2557
mosquito	0.54	0.60	0.57	2527
scorpion	0.72	0.80	0.76	2468
spider	0.69	0.70	0.70	2482
accuracy			0.69	15000
macro avg	0.70	0.69	0.69	15000
weighted avg	0.70	0.69	0.69	15000



Some extension of Receiver operating characteristic to multi-class



One-vs-One ROC AUC scores:
0.914622 (macro),
0.914684 (weighted by prevalence)
One-vs-Rest ROC AUC scores:
0.914652 (macro),
0.914769 (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 14.549 minutes