In [1]:

```
import numpy as np
import pandas as pd
from keras.layers import Dense
from keras.layers import Embedding
from keras.layers import LSTM
from keras.models import Sequential
from keras.utils import to_categorical
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import train_test_split

import itertools

import numpy as np
import pandas as pd
import seaborn as sns
from matplotlib import pyplot as plt

from recipes import plot_confusion_matrix
```

In [2]:

```
def read_crop_list():
    crop_codes = '/media/data/projects/crophisto/crop_codes.csv'

    # load crop info
    df_crops = pd.read_csv(crop_codes, sep=";")
    # transform data to get a line per each
    crop_list = df_crops["code"].to_numpy()
    vocab = {val: idx for idx, val in enumerate(crop_list)}
    return df_crops, vocab
```

In [ ]:

```

```

In [3]:

```
# prepare data

df_crops, vocab = read_crop_list()

data_file = "/media/data/projects/crophisto/data.npy"
data = np.load(data_file)

vocab_size = len(vocab)

# sample data to 10.000
sample_size = 10000
random_indices = np.random.choice(data.shape[0], size=sample_size, replace=False
)
sample = data[random_indices, :]

# sample = data[:1000, :]
y = sample[:, 8]
X = sample[:, 0:8]
sequence_length = X.shape[-1]
y = to_categorical(y, num_classes=vocab_size)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
```

In [4]:

```
# define model
embedding_size = vocab_size
# define the model
model = Sequential()
model.add(Embedding(vocab_size, embedding_size, input_length=sequence_length))
model.add(LSTM(50))
model.add(Dense(vocab_size, activation='sigmoid'))
print(model.summary())

# compile network
model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accur
acy'])
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
embedding (Embedding)        (None, 8, 29)             841       
_________________________________________________________________
lstm (LSTM)                  (None, 50)                16000     
_________________________________________________________________
dense (Dense)                (None, 29)                1479      
=================================================================
Total params: 18,320
Trainable params: 18,320
Non-trainable params: 0
_________________________________________________________________
None
```

In [5]:

```
# train
epochs = 300
model.fit(X, y, epochs=epochs, verbose=2)
```

```
Epoch 1/300
313/313 - 1s - loss: 2.2693 - accuracy: 0.2825
Epoch 2/300
313/313 - 1s - loss: 1.7586 - accuracy: 0.3656
Epoch 3/300
313/313 - 1s - loss: 1.6154 - accuracy: 0.4503
Epoch 4/300
313/313 - 1s - loss: 1.5246 - accuracy: 0.4927
Epoch 5/300
313/313 - 1s - loss: 1.4594 - accuracy: 0.5135
Epoch 6/300
313/313 - 1s - loss: 1.4121 - accuracy: 0.5300
Epoch 7/300
313/313 - 1s - loss: 1.3799 - accuracy: 0.5424
Epoch 8/300
313/313 - 1s - loss: 1.3591 - accuracy: 0.5525
Epoch 9/300
313/313 - 1s - loss: 1.3467 - accuracy: 0.5555
Epoch 10/300
313/313 - 1s - loss: 1.3345 - accuracy: 0.5584
Epoch 11/300
313/313 - 1s - loss: 1.3249 - accuracy: 0.5597
Epoch 12/300
313/313 - 1s - loss: 1.3179 - accuracy: 0.5621
Epoch 13/300
313/313 - 1s - loss: 1.3075 - accuracy: 0.5627
Epoch 14/300
313/313 - 1s - loss: 1.3004 - accuracy: 0.5631
Epoch 15/300
313/313 - 1s - loss: 1.2924 - accuracy: 0.5675
Epoch 16/300
313/313 - 1s - loss: 1.2860 - accuracy: 0.5678
Epoch 17/300
313/313 - 1s - loss: 1.2804 - accuracy: 0.5710
Epoch 18/300
313/313 - 1s - loss: 1.2735 - accuracy: 0.5713
Epoch 19/300
313/313 - 1s - loss: 1.2677 - accuracy: 0.5700
Epoch 20/300
313/313 - 1s - loss: 1.2620 - accuracy: 0.5763
Epoch 21/300
313/313 - 1s - loss: 1.2554 - accuracy: 0.5787
Epoch 22/300
313/313 - 1s - loss: 1.2509 - accuracy: 0.5805
Epoch 23/300
313/313 - 1s - loss: 1.2441 - accuracy: 0.5802
Epoch 24/300
313/313 - 1s - loss: 1.2411 - accuracy: 0.5814
Epoch 25/300
313/313 - 1s - loss: 1.2334 - accuracy: 0.5814
Epoch 26/300
313/313 - 1s - loss: 1.2288 - accuracy: 0.5836
Epoch 27/300
313/313 - 1s - loss: 1.2240 - accuracy: 0.5857
Epoch 28/300
313/313 - 1s - loss: 1.2151 - accuracy: 0.5855
Epoch 29/300
313/313 - 1s - loss: 1.2100 - accuracy: 0.5852
Epoch 30/300
313/313 - 1s - loss: 1.2080 - accuracy: 0.5869
Epoch 31/300
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313/313 - 1s - loss: 1.2019 - accuracy: 0.5885
Epoch 32/300
313/313 - 1s - loss: 1.1953 - accuracy: 0.5909
Epoch 33/300
313/313 - 1s - loss: 1.1909 - accuracy: 0.5899
Epoch 34/300
313/313 - 1s - loss: 1.1854 - accuracy: 0.5959
Epoch 35/300
313/313 - 1s - loss: 1.1813 - accuracy: 0.5959
Epoch 36/300
313/313 - 1s - loss: 1.1727 - accuracy: 0.5984
Epoch 37/300
313/313 - 1s - loss: 1.1686 - accuracy: 0.6010
Epoch 38/300
313/313 - 1s - loss: 1.1630 - accuracy: 0.5992
Epoch 39/300
313/313 - 1s - loss: 1.1564 - accuracy: 0.6027
Epoch 40/300
313/313 - 1s - loss: 1.1500 - accuracy: 0.6035
Epoch 41/300
313/313 - 1s - loss: 1.1467 - accuracy: 0.6061
Epoch 42/300
313/313 - 1s - loss: 1.1393 - accuracy: 0.6115
Epoch 43/300
313/313 - 1s - loss: 1.1344 - accuracy: 0.6068
Epoch 44/300
313/313 - 1s - loss: 1.1268 - accuracy: 0.6112
Epoch 45/300
313/313 - 1s - loss: 1.1218 - accuracy: 0.6134
Epoch 46/300
313/313 - 1s - loss: 1.1160 - accuracy: 0.6132
Epoch 47/300
313/313 - 1s - loss: 1.1091 - accuracy: 0.6191
Epoch 48/300
313/313 - 1s - loss: 1.1046 - accuracy: 0.6177
Epoch 49/300
313/313 - 1s - loss: 1.0947 - accuracy: 0.6216
Epoch 50/300
313/313 - 1s - loss: 1.0910 - accuracy: 0.6200
Epoch 51/300
313/313 - 1s - loss: 1.0841 - accuracy: 0.6203
Epoch 52/300
313/313 - 1s - loss: 1.0781 - accuracy: 0.6296
Epoch 53/300
313/313 - 1s - loss: 1.0749 - accuracy: 0.6252
Epoch 54/300
313/313 - 1s - loss: 1.0654 - accuracy: 0.6290
Epoch 55/300
313/313 - 1s - loss: 1.0608 - accuracy: 0.6327
Epoch 56/300
313/313 - 1s - loss: 1.0542 - accuracy: 0.6331
Epoch 57/300
313/313 - 1s - loss: 1.0473 - accuracy: 0.6368
Epoch 58/300
313/313 - 1s - loss: 1.0415 - accuracy: 0.6350
Epoch 59/300
313/313 - 1s - loss: 1.0347 - accuracy: 0.6370
Epoch 60/300
313/313 - 1s - loss: 1.0279 - accuracy: 0.6386
Epoch 61/300
313/313 - 1s - loss: 1.0247 - accuracy: 0.6418
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Epoch 62/300
313/313 - 1s - loss: 1.0134 - accuracy: 0.6454
Epoch 63/300
313/313 - 1s - loss: 1.0110 - accuracy: 0.6461
Epoch 64/300
313/313 - 1s - loss: 1.0033 - accuracy: 0.6490
Epoch 65/300
313/313 - 1s - loss: 0.9986 - accuracy: 0.6505
Epoch 66/300
313/313 - 1s - loss: 0.9925 - accuracy: 0.6534
Epoch 67/300
313/313 - 1s - loss: 0.9852 - accuracy: 0.6554
Epoch 68/300
313/313 - 1s - loss: 0.9813 - accuracy: 0.6527
Epoch 69/300
313/313 - 1s - loss: 0.9748 - accuracy: 0.6586
Epoch 70/300
313/313 - 1s - loss: 0.9708 - accuracy: 0.6607
Epoch 71/300
313/313 - 1s - loss: 0.9623 - accuracy: 0.6626
Epoch 72/300
313/313 - 1s - loss: 0.9553 - accuracy: 0.6674
Epoch 73/300
313/313 - 1s - loss: 0.9484 - accuracy: 0.6662
Epoch 74/300
313/313 - 1s - loss: 0.9443 - accuracy: 0.6693
Epoch 75/300
313/313 - 1s - loss: 0.9367 - accuracy: 0.6746
Epoch 76/300
313/313 - 1s - loss: 0.9330 - accuracy: 0.6736
Epoch 77/300
313/313 - 1s - loss: 0.9237 - accuracy: 0.6763
Epoch 78/300
313/313 - 1s - loss: 0.9188 - accuracy: 0.6794
Epoch 79/300
313/313 - 1s - loss: 0.9162 - accuracy: 0.6805
Epoch 80/300
313/313 - 1s - loss: 0.9066 - accuracy: 0.6860
Epoch 81/300
313/313 - 1s - loss: 0.9013 - accuracy: 0.6861
Epoch 82/300
313/313 - 1s - loss: 0.8972 - accuracy: 0.6894
Epoch 83/300
313/313 - 1s - loss: 0.8897 - accuracy: 0.6900
Epoch 84/300
313/313 - 1s - loss: 0.8820 - accuracy: 0.6933
Epoch 85/300
313/313 - 1s - loss: 0.8779 - accuracy: 0.6964
Epoch 86/300
313/313 - 1s - loss: 0.8725 - accuracy: 0.6962
Epoch 87/300
313/313 - 1s - loss: 0.8661 - accuracy: 0.7024
Epoch 88/300
313/313 - 1s - loss: 0.8602 - accuracy: 0.7059
Epoch 89/300
313/313 - 1s - loss: 0.8554 - accuracy: 0.7055
Epoch 90/300
313/313 - 1s - loss: 0.8511 - accuracy: 0.7036
Epoch 91/300
313/313 - 1s - loss: 0.8467 - accuracy: 0.7068
Epoch 92/300
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313/313 - 1s - loss: 0.8375 - accuracy: 0.7123
Epoch 93/300
313/313 - 1s - loss: 0.8337 - accuracy: 0.7114
Epoch 94/300
313/313 - 1s - loss: 0.8278 - accuracy: 0.7168
Epoch 95/300
313/313 - 1s - loss: 0.8193 - accuracy: 0.7208
Epoch 96/300
313/313 - 1s - loss: 0.8156 - accuracy: 0.7210
Epoch 97/300
313/313 - 1s - loss: 0.8101 - accuracy: 0.7212
Epoch 98/300
313/313 - 1s - loss: 0.8047 - accuracy: 0.7275
Epoch 99/300
313/313 - 1s - loss: 0.7984 - accuracy: 0.7246
Epoch 100/300
313/313 - 1s - loss: 0.7937 - accuracy: 0.7269
Epoch 101/300
313/313 - 1s - loss: 0.7896 - accuracy: 0.7328
Epoch 102/300
313/313 - 1s - loss: 0.7843 - accuracy: 0.7301
Epoch 103/300
313/313 - 1s - loss: 0.7753 - accuracy: 0.7341
Epoch 104/300
313/313 - 1s - loss: 0.7735 - accuracy: 0.7350
Epoch 105/300
313/313 - 1s - loss: 0.7692 - accuracy: 0.7402
Epoch 106/300
313/313 - 1s - loss: 0.7610 - accuracy: 0.7435
Epoch 107/300
313/313 - 1s - loss: 0.7577 - accuracy: 0.7456
Epoch 108/300
313/313 - 1s - loss: 0.7547 - accuracy: 0.7463
Epoch 109/300
313/313 - 1s - loss: 0.7479 - accuracy: 0.7474
Epoch 110/300
313/313 - 1s - loss: 0.7445 - accuracy: 0.7526
Epoch 111/300
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Epoch 112/300
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Epoch 116/300
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Epoch 117/300
313/313 - 1s - loss: 0.7115 - accuracy: 0.7611
Epoch 118/300
313/313 - 1s - loss: 0.7065 - accuracy: 0.7663
Epoch 119/300
313/313 - 1s - loss: 0.7012 - accuracy: 0.7646
Epoch 120/300
313/313 - 1s - loss: 0.7015 - accuracy: 0.7634
Epoch 121/300
313/313 - 1s - loss: 0.6915 - accuracy: 0.7680
Epoch 122/300
313/313 - 1s - loss: 0.6898 - accuracy: 0.7699
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Epoch 123/300
313/313 - 1s - loss: 0.6814 - accuracy: 0.7726
Epoch 124/300
313/313 - 1s - loss: 0.6811 - accuracy: 0.7701
Epoch 125/300
313/313 - 1s - loss: 0.6754 - accuracy: 0.7737
Epoch 126/300
313/313 - 1s - loss: 0.6737 - accuracy: 0.7767
Epoch 127/300
313/313 - 1s - loss: 0.6657 - accuracy: 0.7743
Epoch 128/300
313/313 - 1s - loss: 0.6639 - accuracy: 0.7799
Epoch 129/300
313/313 - 1s - loss: 0.6612 - accuracy: 0.7777
Epoch 130/300
313/313 - 1s - loss: 0.6559 - accuracy: 0.7800
Epoch 131/300
313/313 - 1s - loss: 0.6503 - accuracy: 0.7819
Epoch 132/300
313/313 - 1s - loss: 0.6490 - accuracy: 0.7829
Epoch 133/300
313/313 - 1s - loss: 0.6384 - accuracy: 0.7864
Epoch 134/300
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Epoch 135/300
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Epoch 136/300
313/313 - 1s - loss: 0.6322 - accuracy: 0.7890
Epoch 137/300
313/313 - 1s - loss: 0.6256 - accuracy: 0.7897
Epoch 138/300
313/313 - 1s - loss: 0.6227 - accuracy: 0.7947
Epoch 139/300
313/313 - 1s - loss: 0.6185 - accuracy: 0.7947
Epoch 140/300
313/313 - 1s - loss: 0.6109 - accuracy: 0.7971
Epoch 141/300
313/313 - 1s - loss: 0.6131 - accuracy: 0.8007
Epoch 142/300
313/313 - 1s - loss: 0.6042 - accuracy: 0.8030
Epoch 143/300
313/313 - 1s - loss: 0.6054 - accuracy: 0.7994
Epoch 144/300
313/313 - 1s - loss: 0.6012 - accuracy: 0.7990
Epoch 145/300
313/313 - 1s - loss: 0.6007 - accuracy: 0.8034
Epoch 146/300
313/313 - 1s - loss: 0.5933 - accuracy: 0.8027
Epoch 147/300
313/313 - 1s - loss: 0.5930 - accuracy: 0.8034
Epoch 148/300
313/313 - 1s - loss: 0.5892 - accuracy: 0.8007
Epoch 149/300
313/313 - 1s - loss: 0.5801 - accuracy: 0.8093
Epoch 150/300
313/313 - 1s - loss: 0.5804 - accuracy: 0.8065
Epoch 151/300
313/313 - 1s - loss: 0.5758 - accuracy: 0.8085
Epoch 152/300
313/313 - 1s - loss: 0.5705 - accuracy: 0.8126
Epoch 153/300
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313/313 - 1s - loss: 0.5707 - accuracy: 0.8111
Epoch 154/300
313/313 - 1s - loss: 0.5645 - accuracy: 0.8123
Epoch 155/300
313/313 - 1s - loss: 0.5676 - accuracy: 0.8102
Epoch 156/300
313/313 - 1s - loss: 0.5646 - accuracy: 0.8149
Epoch 157/300
313/313 - 1s - loss: 0.5573 - accuracy: 0.8172
Epoch 158/300
313/313 - 1s - loss: 0.5512 - accuracy: 0.8175
Epoch 159/300
313/313 - 1s - loss: 0.5501 - accuracy: 0.8202
Epoch 160/300
313/313 - 1s - loss: 0.5436 - accuracy: 0.8219
Epoch 161/300
313/313 - 1s - loss: 0.5500 - accuracy: 0.8176
Epoch 162/300
313/313 - 1s - loss: 0.5414 - accuracy: 0.8211
Epoch 163/300
313/313 - 1s - loss: 0.5376 - accuracy: 0.8205
Epoch 164/300
313/313 - 1s - loss: 0.5332 - accuracy: 0.8239
Epoch 165/300
313/313 - 1s - loss: 0.5326 - accuracy: 0.8241
Epoch 166/300
313/313 - 1s - loss: 0.5285 - accuracy: 0.8243
Epoch 167/300
313/313 - 1s - loss: 0.5210 - accuracy: 0.8309
Epoch 168/300
313/313 - 1s - loss: 0.5228 - accuracy: 0.8266
Epoch 169/300
313/313 - 1s - loss: 0.5183 - accuracy: 0.8292
Epoch 170/300
313/313 - 1s - loss: 0.5176 - accuracy: 0.8317
Epoch 171/300
313/313 - 1s - loss: 0.5157 - accuracy: 0.8276
Epoch 172/300
313/313 - 1s - loss: 0.5092 - accuracy: 0.8319
Epoch 173/300
313/313 - 1s - loss: 0.5117 - accuracy: 0.8309
Epoch 174/300
313/313 - 1s - loss: 0.5038 - accuracy: 0.8336
Epoch 175/300
313/313 - 1s - loss: 0.5011 - accuracy: 0.8344
Epoch 176/300
313/313 - 1s - loss: 0.5024 - accuracy: 0.8321
Epoch 177/300
313/313 - 1s - loss: 0.4957 - accuracy: 0.8374
Epoch 178/300
313/313 - 1s - loss: 0.4917 - accuracy: 0.8393
Epoch 179/300
313/313 - 1s - loss: 0.4953 - accuracy: 0.8337
Epoch 180/300
313/313 - 1s - loss: 0.4912 - accuracy: 0.8373
Epoch 181/300
313/313 - 1s - loss: 0.4903 - accuracy: 0.8360
Epoch 182/300
313/313 - 1s - loss: 0.4845 - accuracy: 0.8394
Epoch 183/300
313/313 - 1s - loss: 0.4786 - accuracy: 0.8450
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Epoch 184/300
313/313 - 1s - loss: 0.4816 - accuracy: 0.8421
Epoch 185/300
313/313 - 1s - loss: 0.4713 - accuracy: 0.8441
Epoch 186/300
313/313 - 1s - loss: 0.4733 - accuracy: 0.8421
Epoch 187/300
313/313 - 1s - loss: 0.4699 - accuracy: 0.8447
Epoch 188/300
313/313 - 1s - loss: 0.4716 - accuracy: 0.8426
Epoch 189/300
313/313 - 1s - loss: 0.4627 - accuracy: 0.8485
Epoch 190/300
313/313 - 1s - loss: 0.4642 - accuracy: 0.8470
Epoch 191/300
313/313 - 1s - loss: 0.4636 - accuracy: 0.8483
Epoch 192/300
313/313 - 1s - loss: 0.4569 - accuracy: 0.8538
Epoch 193/300
313/313 - 1s - loss: 0.4588 - accuracy: 0.8481
Epoch 194/300
313/313 - 1s - loss: 0.4526 - accuracy: 0.8498
Epoch 195/300
313/313 - 1s - loss: 0.4498 - accuracy: 0.8527
Epoch 196/300
313/313 - 1s - loss: 0.4516 - accuracy: 0.8519
Epoch 197/300
313/313 - 1s - loss: 0.4502 - accuracy: 0.8496
Epoch 198/300
313/313 - 1s - loss: 0.4437 - accuracy: 0.8540
Epoch 199/300
313/313 - 1s - loss: 0.4416 - accuracy: 0.8542
Epoch 200/300
313/313 - 1s - loss: 0.4356 - accuracy: 0.8562
Epoch 201/300
313/313 - 1s - loss: 0.4338 - accuracy: 0.8559
Epoch 202/300
313/313 - 1s - loss: 0.4338 - accuracy: 0.8566
Epoch 203/300
313/313 - 1s - loss: 0.4343 - accuracy: 0.8567
Epoch 204/300
313/313 - 1s - loss: 0.4313 - accuracy: 0.8585
Epoch 205/300
313/313 - 1s - loss: 0.4349 - accuracy: 0.8552
Epoch 206/300
313/313 - 1s - loss: 0.4386 - accuracy: 0.8553
Epoch 207/300
313/313 - 1s - loss: 0.4288 - accuracy: 0.8597
Epoch 208/300
313/313 - 1s - loss: 0.4154 - accuracy: 0.8649
Epoch 209/300
313/313 - 1s - loss: 0.4258 - accuracy: 0.8606
Epoch 210/300
313/313 - 1s - loss: 0.4275 - accuracy: 0.8624
Epoch 211/300
313/313 - 1s - loss: 0.4130 - accuracy: 0.8661
Epoch 212/300
313/313 - 1s - loss: 0.4144 - accuracy: 0.8638
Epoch 213/300
313/313 - 1s - loss: 0.4108 - accuracy: 0.8644
Epoch 214/300
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313/313 - 1s - loss: 0.4097 - accuracy: 0.8665
Epoch 215/300
313/313 - 1s - loss: 0.4031 - accuracy: 0.8705
Epoch 216/300
313/313 - 1s - loss: 0.4099 - accuracy: 0.8662
Epoch 217/300
313/313 - 1s - loss: 0.4001 - accuracy: 0.8683
Epoch 218/300
313/313 - 1s - loss: 0.4061 - accuracy: 0.8667
Epoch 219/300
313/313 - 1s - loss: 0.4051 - accuracy: 0.8692
Epoch 220/300
313/313 - 1s - loss: 0.4029 - accuracy: 0.8682
Epoch 221/300
313/313 - 1s - loss: 0.3953 - accuracy: 0.8708
Epoch 222/300
313/313 - 1s - loss: 0.3925 - accuracy: 0.8748
Epoch 223/300
313/313 - 1s - loss: 0.3937 - accuracy: 0.8727
Epoch 224/300
313/313 - 1s - loss: 0.3940 - accuracy: 0.8722
Epoch 225/300
313/313 - 1s - loss: 0.3855 - accuracy: 0.8746
Epoch 226/300
313/313 - 1s - loss: 0.3882 - accuracy: 0.8736
Epoch 227/300
313/313 - 1s - loss: 0.3886 - accuracy: 0.8703
Epoch 228/300
313/313 - 1s - loss: 0.3856 - accuracy: 0.8730
Epoch 229/300
313/313 - 1s - loss: 0.3874 - accuracy: 0.8736
Epoch 230/300
313/313 - 1s - loss: 0.3838 - accuracy: 0.8744
Epoch 231/300
313/313 - 1s - loss: 0.3776 - accuracy: 0.8760
Epoch 232/300
313/313 - 1s - loss: 0.3746 - accuracy: 0.8780
Epoch 233/300
313/313 - 1s - loss: 0.3734 - accuracy: 0.8790
Epoch 234/300
313/313 - 1s - loss: 0.3769 - accuracy: 0.8744
Epoch 235/300
313/313 - 1s - loss: 0.3818 - accuracy: 0.8732
Epoch 236/300
313/313 - 1s - loss: 0.3672 - accuracy: 0.8831
Epoch 237/300
313/313 - 1s - loss: 0.3634 - accuracy: 0.8813
Epoch 238/300
313/313 - 1s - loss: 0.3656 - accuracy: 0.8808
Epoch 239/300
313/313 - 1s - loss: 0.3667 - accuracy: 0.8806
Epoch 240/300
313/313 - 1s - loss: 0.3698 - accuracy: 0.8809
Epoch 241/300
313/313 - 1s - loss: 0.3677 - accuracy: 0.8794
Epoch 242/300
313/313 - 1s - loss: 0.3621 - accuracy: 0.8830
Epoch 243/300
313/313 - 1s - loss: 0.3563 - accuracy: 0.8862
Epoch 244/300
313/313 - 1s - loss: 0.3677 - accuracy: 0.8794
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Epoch 245/300
313/313 - 1s - loss: 0.3559 - accuracy: 0.8872
Epoch 246/300
313/313 - 1s - loss: 0.3622 - accuracy: 0.8815
Epoch 247/300
313/313 - 1s - loss: 0.3581 - accuracy: 0.8837
Epoch 248/300
313/313 - 1s - loss: 0.3551 - accuracy: 0.8834
Epoch 249/300
313/313 - 1s - loss: 0.3519 - accuracy: 0.8871
Epoch 250/300
313/313 - 1s - loss: 0.3496 - accuracy: 0.8868
Epoch 251/300
313/313 - 1s - loss: 0.3451 - accuracy: 0.8877
Epoch 252/300
313/313 - 1s - loss: 0.3509 - accuracy: 0.8876
Epoch 253/300
313/313 - 1s - loss: 0.3566 - accuracy: 0.8862
Epoch 254/300
313/313 - 1s - loss: 0.3516 - accuracy: 0.8832
Epoch 255/300
313/313 - 1s - loss: 0.3457 - accuracy: 0.8860
Epoch 256/300
313/313 - 1s - loss: 0.3494 - accuracy: 0.8836
Epoch 257/300
313/313 - 1s - loss: 0.3379 - accuracy: 0.8936
Epoch 258/300
313/313 - 1s - loss: 0.3314 - accuracy: 0.8929
Epoch 259/300
313/313 - 1s - loss: 0.3300 - accuracy: 0.8965
Epoch 260/300
313/313 - 1s - loss: 0.3365 - accuracy: 0.8912
Epoch 261/300
313/313 - 1s - loss: 0.3395 - accuracy: 0.8914
Epoch 262/300
313/313 - 1s - loss: 0.3433 - accuracy: 0.8865
Epoch 263/300
313/313 - 1s - loss: 0.3355 - accuracy: 0.8885
Epoch 264/300
313/313 - 1s - loss: 0.3287 - accuracy: 0.8949
Epoch 265/300
313/313 - 1s - loss: 0.3298 - accuracy: 0.8930
Epoch 266/300
313/313 - 1s - loss: 0.3301 - accuracy: 0.8923
Epoch 267/300
313/313 - 1s - loss: 0.3225 - accuracy: 0.8936
Epoch 268/300
313/313 - 1s - loss: 0.3293 - accuracy: 0.8928
Epoch 269/300
313/313 - 1s - loss: 0.3404 - accuracy: 0.8871
Epoch 270/300
313/313 - 1s - loss: 0.3263 - accuracy: 0.8947
Epoch 271/300
313/313 - 1s - loss: 0.3189 - accuracy: 0.8975
Epoch 272/300
313/313 - 1s - loss: 0.3167 - accuracy: 0.8967
Epoch 273/300
313/313 - 1s - loss: 0.3290 - accuracy: 0.8923
Epoch 274/300
313/313 - 1s - loss: 0.3421 - accuracy: 0.8891
Epoch 275/300
```

```
313/313 - 1s - loss: 0.3433 - accuracy: 0.8856
Epoch 276/300
313/313 - 1s - loss: 0.3215 - accuracy: 0.8962
Epoch 277/300
313/313 - 1s - loss: 0.3147 - accuracy: 0.8968
Epoch 278/300
313/313 - 1s - loss: 0.3096 - accuracy: 0.8996
Epoch 279/300
313/313 - 1s - loss: 0.3093 - accuracy: 0.8997
Epoch 280/300
313/313 - 1s - loss: 0.3088 - accuracy: 0.8996
Epoch 281/300
313/313 - 1s - loss: 0.3102 - accuracy: 0.9007
Epoch 282/300
313/313 - 1s - loss: 0.3116 - accuracy: 0.8998
Epoch 283/300
313/313 - 1s - loss: 0.3114 - accuracy: 0.9006
Epoch 284/300
313/313 - 1s - loss: 0.3146 - accuracy: 0.8967
Epoch 285/300
313/313 - 1s - loss: 0.3177 - accuracy: 0.8981
Epoch 286/300
313/313 - 1s - loss: 0.2995 - accuracy: 0.9034
Epoch 287/300
313/313 - 1s - loss: 0.3001 - accuracy: 0.9019
Epoch 288/300
313/313 - 1s - loss: 0.3072 - accuracy: 0.9002
Epoch 289/300
313/313 - 1s - loss: 0.3140 - accuracy: 0.8977
Epoch 290/300
313/313 - 1s - loss: 0.2998 - accuracy: 0.9044
Epoch 291/300
313/313 - 1s - loss: 0.3035 - accuracy: 0.9013
Epoch 292/300
313/313 - 1s - loss: 0.3057 - accuracy: 0.8998
Epoch 293/300
313/313 - 1s - loss: 0.3034 - accuracy: 0.9042
Epoch 294/300
313/313 - 1s - loss: 0.2928 - accuracy: 0.9031
Epoch 295/300
313/313 - 1s - loss: 0.2979 - accuracy: 0.9046
Epoch 296/300
313/313 - 1s - loss: 0.3100 - accuracy: 0.8990
Epoch 297/300
313/313 - 1s - loss: 0.3030 - accuracy: 0.8999
Epoch 298/300
313/313 - 1s - loss: 0.2906 - accuracy: 0.9054
Epoch 299/300
313/313 - 1s - loss: 0.2975 - accuracy: 0.9050
Epoch 300/300
313/313 - 1s - loss: 0.2918 - accuracy: 0.9022
```

Out[5]:

```
<tensorflow.python.keras.callbacks.History at 0x7ff3ac3430b8>
```

In [6]:

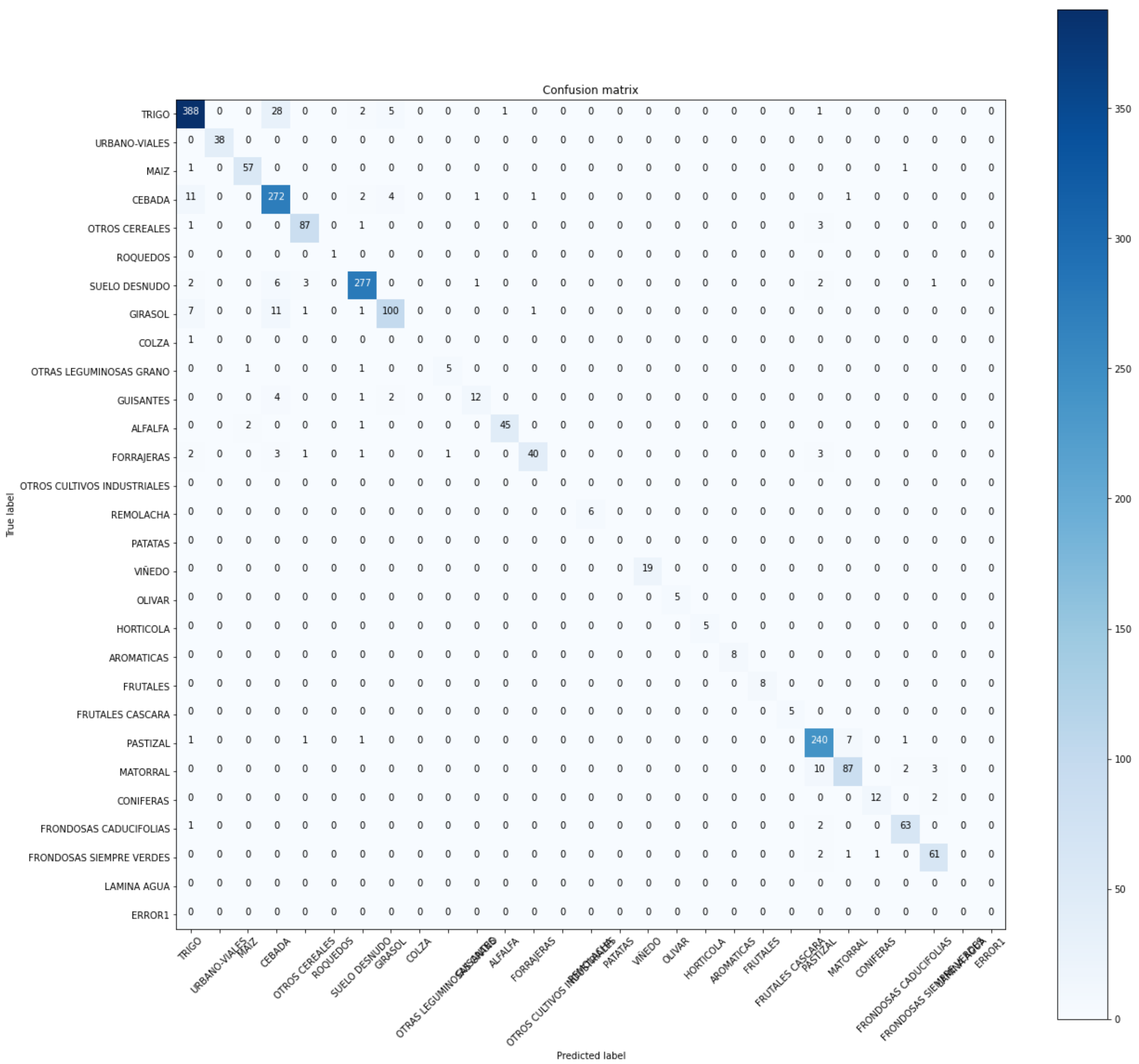
```
# evaluate
loss = model.evaluate(X_test, y_test, verbose=0)
print("Loss on test data: {}".format(loss))

y_hat = model.predict(X_test)
croplist = df_crops["description"].values.tolist()

class_test = np.argmax(y_test, axis=1)
class_predicted = np.argmax(y_hat, axis=1)

crop_list = np.unique(data)
crop_names = df_crops["description"].values.tolist()
cfm = confusion_matrix(class_test, class_predicted, crop_list)
```

```
Loss on test data: [0.2564406096935272, 0.9204999804496765]

/home/gus/workspaces/wpy/venvs/mathor/lib/python3.6/site-packages/sk
learn/utils/validation.py:71: FutureWarning: Pass labels=[ 0  1  2
3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21 22 23
 24 25 26 27 28] as keyword args. From version 0.25 passing these as
positional arguments will result in an error
  FutureWarning)
```

In [7]:

```
from matplotlib import pyplot as plt
plt.figure(figsize=(20, 20))

plot_confusion_matrix(cfm, classes=crop_names)
```

Confusion matrix, without normalization



from sklearn.metrics import classification_report

report = classification_report(y_test,y_hat)

In [13]:

```
from sklearn.metrics import classification_report
report = classification_report(class_test, class_predicted, labels=crop_list, ta
rget_names =crop_names)
print(report)
```

```
                              precision    recall  f1-score   support

                        TRIGO       0.93      0.91      0.92       425
               URBANO-VIALES       1.00      1.00      1.00        38
                         MAIZ       0.95      0.97      0.96        59
                       CEBADA       0.84      0.93      0.88       292
              OTROS CEREALES       0.94      0.95      0.94        92
                    ROQUEDOS       1.00      1.00      1.00         1
               SUELO DESNUDO       0.96      0.95      0.96       292
                     GIRASOL       0.90      0.83      0.86       121
                       COLZA       0.00      0.00      0.00         1
     OTRAS LEGUMINOSAS GRANO       0.83      0.71      0.77         7
                   GUISANTES       0.86      0.63      0.73        19
                     ALFALFA       0.98      0.94      0.96        48
                  FORRAJERAS       0.95      0.78      0.86        51
OTROS CULTIVOS INDUSTRIALES       0.00      0.00      0.00         0
                   REMOLACHA       1.00      1.00      1.00         6
                     PATATAS       0.00      0.00      0.00         0
                      VIÑEDO       1.00      1.00      1.00        19
                      OLIVAR       1.00      1.00      1.00         5
                   HORTICOLA       1.00      1.00      1.00         5
                  AROMATICAS       1.00      1.00      1.00         8
                    FRUTALES       1.00      1.00      1.00         8
            FRUTALES CASCARA       1.00      1.00      1.00         5
                    PASTIZAL       0.91      0.96      0.93       251
                    MATORRAL       0.91      0.85      0.88       102
                   CONIFERAS       0.92      0.86      0.89        14
       FRONDOSAS CADUCIFOLIAS       0.94      0.95      0.95        66
     FRONDOSAS SIEMPRE VERDES       0.91      0.94      0.92        65
                  LAMINA AGUA       0.00      0.00      0.00         0
                      ERROR1       0.00      0.00      0.00         0

                    micro avg       0.92      0.92      0.92      2000
                    macro avg       0.78      0.76      0.77      2000
                 weighted avg       0.92      0.92      0.92      2000

/home/gus/workspaces/wpy/venvs/mathor/lib/python3.6/site-packages/sk
learn/metrics/_classification.py:1221: UndefinedMetricWarning: Recal
l and F-score are ill-defined and being set to 0.0 in labels with no
true samples. Use `zero_division` parameter to control this behavio
r.
  _warn_prf(average, modifier, msg_start, len(result))
```