In [ ]:
```
pip install tensorflow
```

In [ ]:
```
pip install sklearn
```

In [ ]:
```
pip install matplotlib
```

In [ ]:
```
pip install keras
```

In [ ]:
```
pip install seaborn
```

In [ ]:
```
pip install pydotplus
```

In [26]:
```
import matplotlib.pyplot as plt
from PIL import Image
import seaborn as sns
import numpy as np
import pandas as pd
import os
from tensorflow.keras.utils import to_categorical
from glob import glob


from sklearn.model_selection import train_test_split
import keras
from keras.models import Sequential
from keras.layers import Dense, Dropout
import tensorflow as tf
from sklearn.preprocessing import StandardScaler
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, classification_repo
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import ReduceLROnPlateau
from tensorflow.keras import layers
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten

from sklearn.metrics import confusion_matrix
import itertools
import matplotlib.pyplot as plt

import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```
df = pd.read_csv('skinCancer/HAM10000_metadata_Incereased.csv')
df.head(10)
```

Out[2]:

	lesion_id	image_id	dx	dx_type	age	sex	localization
0	HAM_0000118	ISIC_0027419	bkl	histo	80.0	male	scalp
1	HAM_0000118	ISIC_0025030	bkl	histo	80.0	male	scalp
2	HAM_0002730	ISIC_0026769	bkl	histo	80.0	male	scalp
3	HAM_0002730	ISIC_0025661	bkl	histo	80.0	male	scalp
4	HAM_0001466	ISIC_0031633	bkl	histo	75.0	male	ear
5	HAM_0001466	ISIC_0027850	bkl	histo	75.0	male	ear
6	HAM_0002761	ISIC_0029176	bkl	histo	60.0	male	face
7	HAM_0002761	ISIC_0029068	bkl	histo	60.0	male	face
8	HAM_0005132	ISIC_0025837	bkl	histo	70.0	female	back
9	HAM_0005132	ISIC_0025209	bkl	histo	70.0	female	back

In [3]:
```
df.isnull().sum()
```

Out[3]:
```
lesion_id         0
image_id          0
dx                0
dx_type           0
age             119
sex               0
localization      0
dtype: int64
```

In [4]:
```
df.count()
```

Out[4]:
```
lesion_id       49517
image_id        49517
dx              49517
dx_type         49517
age             49398
sex             49517
localization    49517
dtype: int64
```

In [5]:
```
df['age'].fillna(int(df['age'].mean()),inplace=True)
df.isnull().sum()
```

Out[5]:
```
lesion_id       0
image_id        0
dx              0
dx_type         0
age             0
sex             0
localization    0
dtype: int64
```

In [6]:
```
lesion_type_dict = {
    'nv': 'Melanocytic nevi',
    'mel': 'Melanoma',
    'bkl': 'Benign keratosis-like lesions ',
    'bcc': 'Basal cell carcinoma',
    'akiec': 'Actinic keratoses',
    'vasc': 'Vascular lesions',
    'df': 'Dermatofibroma'
}
base_skin_dir = 'skinCancer'

imageid_path_dict = {os.path.splitext(os.path.basename(x))[0]: x
                     for x in glob(os.path.join(base_skin_dir, '*', '*.jpg'))}
```

In [7]:
```
df['path'] = df['image_id'].map(imageid_path_dict.get)
df['cell_type'] = df['dx'].map(lesion_type_dict.get)
df['cell_type_idx'] = pd.Categorical(df['cell_type']).codes
df.head()
```

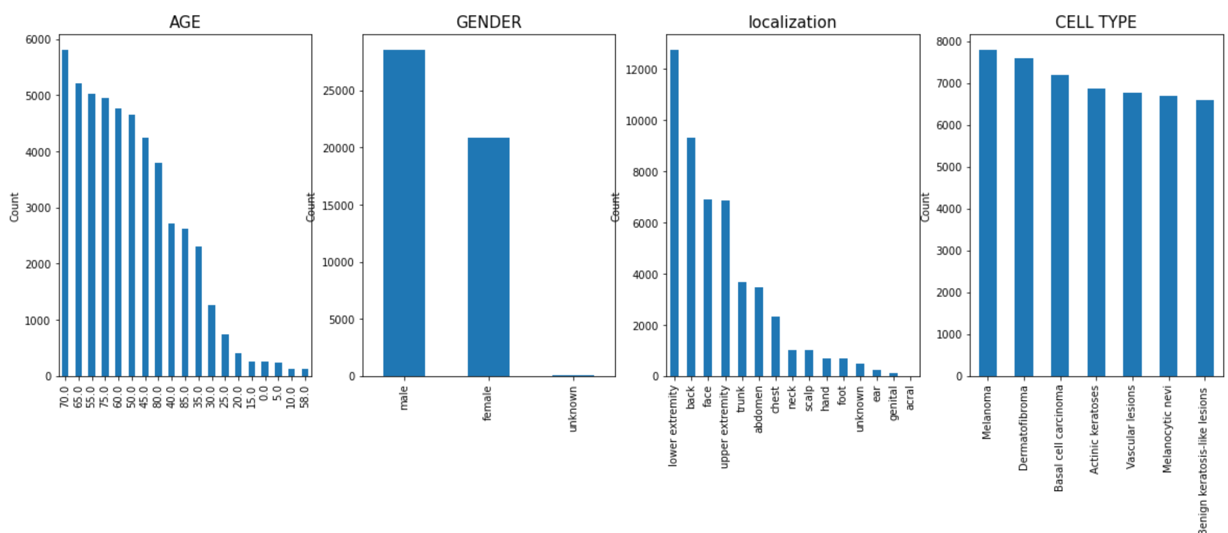
Out[7]:

	lesion_id	image_id	dx	dx_type	age	sex	localization	
0	HAM_0000118	ISIC_0027419	bkl	histo	80.0	male	scalp	skinCancer\HAM10000_images_
1	HAM_0000118	ISIC_0025030	bkl	histo	80.0	male	scalp	skinCancer\HAM10000_images_
2	HAM_0002730	ISIC_0026769	bkl	histo	80.0	male	scalp	skinCancer\HAM10000_images_
3	HAM_0002730	ISIC_0025661	bkl	histo	80.0	male	scalp	skinCancer\HAM10000_images_
4	HAM_0001466	ISIC_0031633	bkl	histo	75.0	male	ear	skinCancer\HAM10000_images_

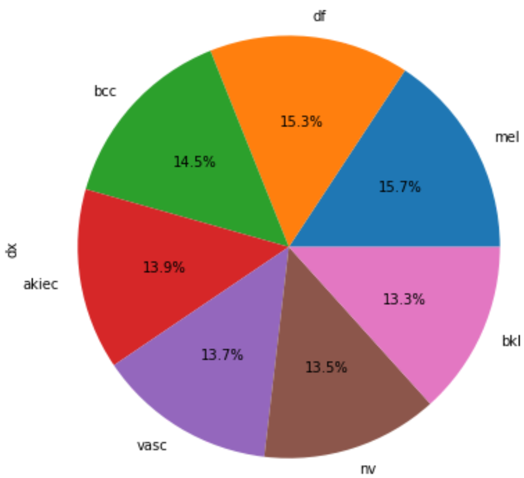
In [8]:
```
df['image'] = df['path'].map(lambda x: np.asarray(Image.open(x).resize((125,100)))
```

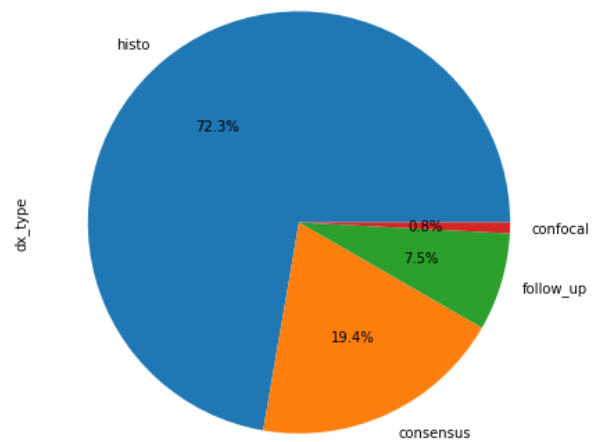
In [9]:
```
plt.figure(figsize=(20,10))
plt.subplots_adjust(left=0.125, bottom=1, right=0.9, top=2, hspace=0.2)
plt.subplot(2,4,1)
plt.title("AGE",fontsize=15)
plt.ylabel("Count")
df['age'].value_counts().plot.bar()

plt.subplot(2,4,2)
plt.title("GENDER",fontsize=15)
plt.ylabel("Count")
df['sex'].value_counts().plot.bar()

plt.subplot(2,4,3)
plt.title("localization",fontsize=15)
plt.ylabel("Count")
plt.xticks(rotation=45)
df['localization'].value_counts().plot.bar()

plt.subplot(2,4,4)
plt.title("CELL TYPE",fontsize=15)
plt.ylabel("Count")
df['cell_type'].value_counts().plot.bar()
```

Out[9]: <AxesSubplot:title={'center':'CELL TYPE'}, ylabel='Count'>



In [10]:
```
plt.figure(figsize=(15,10))
plt.subplot(1,2,1)
df['dx'].value_counts().plot.pie(autopct="%1.1f%%")
plt.subplot(1,2,2)
df['dx_type'].value_counts().plot.pie(autopct="%1.1f%%")
plt.show()
```





In [11]:
```
features=df.drop(columns=['cell_type_idx','image_id'],axis=1)
target=df['cell_type_idx']
features.head()
```

Out[11]:

	lesion_id	dx	dx_type	age	sex	localization	
0	HAM_0000118	bkl	histo	80.0	male	scalp	skinCancer\HAM10000_images_part_1\ISIC_002
1	HAM_0000118	bkl	histo	80.0	male	scalp	skinCancer\HAM10000_images_part_1\ISIC_002
2	HAM_0002730	bkl	histo	80.0	male	scalp	skinCancer\HAM10000_images_part_1\ISIC_002
3	HAM_0002730	bkl	histo	80.0	male	scalp	skinCancer\HAM10000_images_part_1\ISIC_002
4	HAM_0001466	bkl	histo	75.0	male	ear	skinCancer\HAM10000_images_part_2\ISIC_003

In [12]:
```
x_train_o, x_test_o, y_train_o, y_test_o = train_test_split(features, target, tes
tf.unique(x_train_o.cell_type.values)
```

Out[12]:
```
Unique(y=<tf.Tensor: shape=(7,), dtype=string, numpy=
array([b'Actinic keratoses', b'Basal cell carcinoma', b'Dermatofibroma',
       b'Melanoma', b'Benign keratosis-like lesions ',
       b'Melanocytic nevi', b'Vascular lesions'], dtype=object)>, idx=<tf.Tenso
r: shape=(37137,), dtype=int32, numpy=array([0, 1, 1, ..., 1, 1, 6])>)
```

In [13]:
```
x_train = np.asarray(x_train_o['image'].tolist())
x_test = np.asarray(x_test_o['image'].tolist())

x_train_mean = np.mean(x_train)
x_train_std = np.std(x_train)


x_test_mean = np.mean(x_test)
x_test_std = np.std(x_test)

x_train = (x_train - x_train_mean)/x_train_std
x_test = (x_test - x_test_mean)/x_test_std
```

In [14]:
```
# Perform one-hot encoding on the labels
y_train = to_categorical(y_train_o, num_classes = 7)
y_test = to_categorical(y_test_o, num_classes = 7)
y_test
```

Out[14]:
```
array([[0., 0., 0., ..., 0., 1., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 1.],
       ...,
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 1.],
       [0., 0., 0., ..., 0., 0., 0.]], dtype=float32)
```

In [15]:
```
y_test[1]
```

Out[15]:
```
array([0., 0., 0., 1., 0., 0., 0.], dtype=float32)
```

In [16]:
```
y_train
```

Out[16]:
```
array([[1., 0., 0., ..., 0., 0., 0.],
       [0., 1., 0., ..., 0., 0., 0.],
       [0., 1., 0., ..., 0., 0., 0.],
       ...,
       [0., 1., 0., ..., 0., 0., 0.],
       [0., 1., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 1.]], dtype=float32)
```

In [17]:
```
y_test_o.value_counts()
```

Out[17]:
```
5    1924
3    1907
1    1750
0    1730
6    1697
2    1689
4    1683
Name: cell_type_idx, dtype: int64
```

In [18]:
```
# x_train, x_validate, y_train, y_validate = train_test_split(x_train, y_train, t


# Reshape image in 3 dimensions (height = 100, width = 125 , canal = 3)
x_train = x_train.reshape(x_train_o.shape[0], *(100, 125, 3))
x_test = x_test.reshape(x_test_o.shape[0], *(100, 125, 3))
```

In [19]:
```
x_train = x_train.reshape(x_train.shape[0],125*100*3)
x_test = x_test.reshape(x_test.shape[0],125*100*3)
print(x_train.shape)
print(x_test.shape)
```

```
(37137, 37500)
(12380, 37500)
```

In [20]:
```
print(x_train)
```

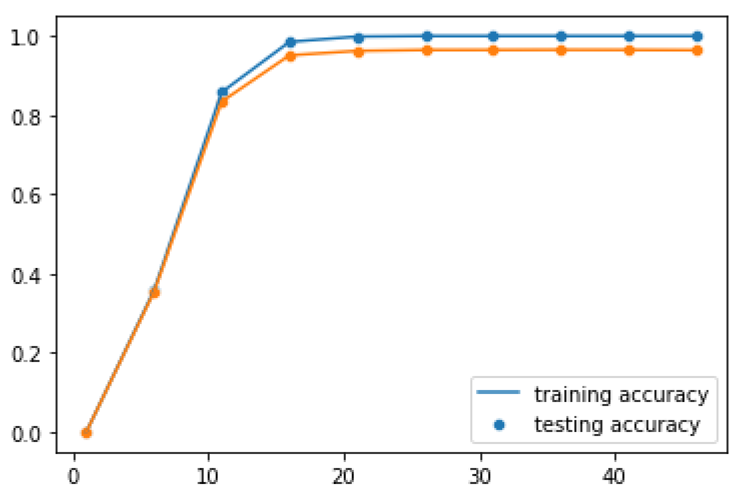
```
[[ 0.67592044 -0.3525907   0.07794885 ...  0.96294681  0.12578657
   0.31713748]
 [-0.04164547 -0.85488684 -1.54853389 ...  0.1736243  -0.6874548
  -1.14191321]
 [ 0.07794885 -1.33326412 -1.45285844 ...  0.60416385 -0.23299638
  -0.16123979]
 ...
 [-2.93582799 -3.31852981 -2.79231481 ... -3.17501663 -3.41420527
  -3.03150345]
 [ 0.53240726 -0.63961707 -0.71137366 ...  0.19754317 -1.02231889
  -1.14191321]
 [ 0.93902794 -0.30475297  0.19754317 ...  0.65200158 -0.63961707
  -0.23299638]]
```

Decision Tree

In [24]:
```
depth = range(1,51,5)
testing_accuracy = []
training_accuracy = []
score = 0

for i in depth:
    tree = DecisionTreeClassifier(max_depth = i, criterion = 'entropy')
    tree.fit(x_train, y_train)

    y_predict_train = tree.predict(x_train)
    training_accuracy.append(accuracy_score(y_train, y_predict_train))

    y_predict_test = tree.predict(x_test)
    acc_score = accuracy_score(y_test,y_predict_test)
    testing_accuracy.append(acc_score)

    print(i)

    if score < acc_score:
        score = acc_score
        best_depth = i

sns.lineplot(depth, training_accuracy)
sns.scatterplot(depth, training_accuracy)
sns.lineplot(depth, testing_accuracy)
sns.scatterplot(depth, testing_accuracy)
plt.legend(['training accuracy', 'testing accuracy'])
```

```
1
6
11
16
21
26
31
36
41
46
```

Out[24]: <matplotlib.legend.Legend at 0x14e31eaed90>



In [25]:
```
print('This is the best depth for Decision Tree Classifier: ', best_depth, '\nAcc
result = confusion_matrix(y_test.argmax(axis=1), y_predict_test.argmax(axis=1),)
print("Confusion Matrix:","\n", result)
report = classification_report(y_test.argmax(axis=1), y_predict_test.argmax(axis=
print("Classification Report:" , "\n", report)
```

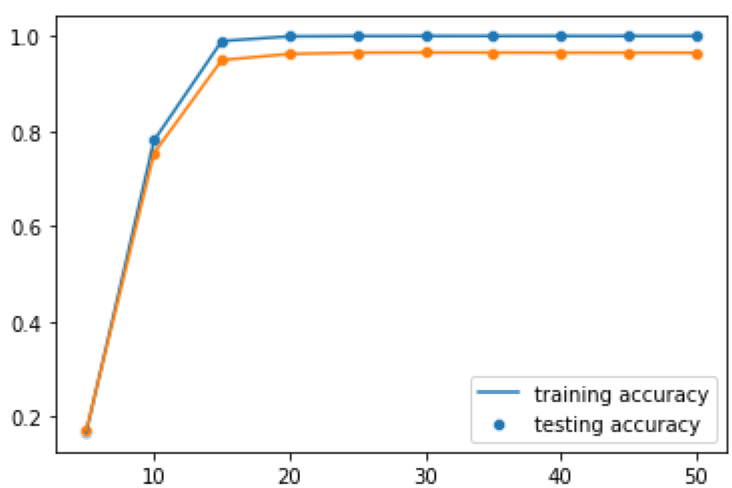
```
This is the best depth for Decision Tree Classifier:  36
Accuracy score is:  0.9651050080775444
Confusion Matrix:
 [[1702    0    7    0   21    0    0]
 [   0 1736    0    0   11    0    3]
 [   0    0 1689    0    0    0    0]
 [   0    0    0 1907    0    0    0]
 [  22   41  126    7 1284  176   27]
 [   0    0    2    0    0 1922    0]
 [   0    0    0    0    0    0 1697]]
Classification Report:
               precision    recall  f1-score   support

           0       0.99      0.98      0.99      1730
           1       0.98      0.99      0.98      1750
           2       0.93      1.00      0.96      1689
           3       1.00      1.00      1.00      1907
           4       0.98      0.76      0.86      1683
           5       0.92      1.00      0.96      1924
           6       0.98      1.00      0.99      1697

    accuracy                           0.96     12380
   macro avg       0.97      0.96      0.96     12380
weighted avg       0.97      0.96      0.96     12380
```

Random Forest

In [26]:
```
#random Forest
depth = range(5,51,5)
testing_accuracy = []
training_accuracy = []
score = 0

for i in depth:
    tree = RandomForestClassifier(max_depth = i, criterion = 'gini', random_state
    tree.fit(x_train, y_train)

    y_predict_train = tree.predict(x_train)
    training_accuracy.append(accuracy_score(y_train, y_predict_train))

    y_predict_test = tree.predict(x_test)
    acc_score = accuracy_score(y_test,y_predict_test)
    testing_accuracy.append(acc_score)

    print(i)

    if score < acc_score:
        score = acc_score
        best_depth = i

sns.lineplot(depth, training_accuracy)
sns.scatterplot(depth, training_accuracy)
sns.lineplot(depth, testing_accuracy)
sns.scatterplot(depth, testing_accuracy)
plt.legend(['training accuracy', 'testing accuracy'])
```

```
5
10
15
20
25
30
35
40
45
50
```

Out[26]: <matplotlib.legend.Legend at 0x14e31f2f880>



In [27]:
```
print('This is the best depth for Decision Tree Classifier: ', best_depth, '\nAcc
result = confusion_matrix(y_test.argmax(axis=1), y_predict_test.argmax(axis=1),)
print("Confusion Matrix:","\n", result)
report = classification_report(y_test.argmax(axis=1), y_predict_test.argmax(axis=
print("Classification Report:" , "\n", report)
```

```
This is the best depth for Decision Tree Classifier:  30
Accuracy score is:  0.9652665589660743
Confusion Matrix:
 [[1730    0    0    0    0    0    0]
 [   0 1750    0    0    0    0    0]
 [   0    0 1689    0    0    0    0]
 [   0    0    0 1907    0    0    0]
 [ 398    3   15    0 1245   22    0]
 [   0    0    0    0    0 1924    0]
 [   0    0    0    0    0    0 1697]]
Classification Report:
               precision    recall  f1-score   support

           0       0.81      1.00      0.90      1730
           1       1.00      1.00      1.00      1750
           2       0.99      1.00      1.00      1689
           3       1.00      1.00      1.00      1907
           4       1.00      0.74      0.85      1683
           5       0.99      1.00      0.99      1924
           6       1.00      1.00      1.00      1697

    accuracy                           0.96     12380
   macro avg       0.97      0.96      0.96     12380
weighted avg       0.97      0.96      0.96     12380
```

KNN

In [ ]:
```
k = range(1,500,2)
testing_accuracy = []
training_accuracy = []
score = 0

for i in k:
    knn = KNeighborsClassifier(n_neighbors = i)
    knn.fit(x_train, y_train)

    y_predict_train = knn.predict(x_train)
    training_accuracy.append(accuracy_score(y_train, y_predict_train))

    y_predict_test = knn.predict(x_test)
    acc_score = accuracy_score(y_test,y_predict_test)
    testing_accuracy.append(acc_score)

    print(i)

    if score < acc_score:
        score = acc_score
        best_k = i


sns.lineplot(k, training_accuracy)
sns.scatterplot(k, training_accuracy)
sns.lineplot(k, testing_accuracy)
sns.scatterplot(k, testing_accuracy)
plt.legend(['training accuracy', 'testing accuracy'])
```

```
1
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```

```
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137
139
141
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145
147
149
151
153
155
157
159
161
163
165
167
```

In [ ]:
```
'''print('This is the best depth for Decision Tree Classifier: ', best_depth, '\r
result = confusion_matrix(y_test.argmax(axis=1), y_predict_test.argmax(axis=1),)
print("Confusion Matrix:","\n", result)
report = classification_report(y_test.argmax(axis=1), y_predict_test.argmax(axis=
print("Classification Report:" , "\n", report)
```

In [41]:
```
x_train = x_train.reshape(x_train_o.shape[0], *(100, 125, 3))
x_test = x_test.reshape(x_test_o.shape[0], *(100, 125, 3))
x_train.shape
```

Out[41]:
```
(37137, 100, 125, 3)
```

MLP

In [42]:
```
x_train = x_train.reshape(x_train.shape[0],125*100*3)
x_test = x_test.reshape(x_test.shape[0],125*100*3)

# define the keras model
model = Sequential()

model.add(Dense(units= 128, kernel_initializer = 'uniform', activation = 'relu',
model.add(Dense(units= 256, kernel_initializer = 'uniform', activation = 'relu'))
model.add(Dense(units= 512, kernel_initializer = 'uniform', activation = 'relu'))
model.add(Dense(units= 64, kernel_initializer = 'uniform', activation = 'relu'))
model.add(Dense(units = 7, kernel_initializer = 'uniform', activation = 'softmax'
model.summary()
```

```
Model: "sequential_4"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_16 (Dense)            (None, 128)               4800128

 dense_17 (Dense)            (None, 256)               33024

 dense_18 (Dense)            (None, 512)               131584

 dense_19 (Dense)            (None, 64)                32832

 dense_20 (Dense)            (None, 7)                 455

=================================================================
Total params: 4,998,023
Trainable params: 4,998,023
Non-trainable params: 0
_________________________________________________________________
```

In [44]:
```
# compile the keras model
model.compile(optimizer = "Adam", loss = 'categorical_crossentropy', metrics = ['

# fit the keras model on the dataset
history = model.fit(x_train, y_train, batch_size = 500, epochs = 25)
```

```
Epoch 1/25
75/75 [==============================] - 10s 121ms/step - loss: 1.1428 - accura
cy: 0.5539
Epoch 2/25
75/75 [==============================] - 8s 112ms/step - loss: 0.6291 - accurac
y: 0.7566
Epoch 3/25
75/75 [==============================] - 8s 110ms/step - loss: 0.4084 - accurac
y: 0.8398
Epoch 4/25
75/75 [==============================] - 8s 111ms/step - loss: 0.3396 - accurac
y: 0.8653
Epoch 5/25
75/75 [==============================] - 8s 111ms/step - loss: 0.2478 - accurac
y: 0.9056
Epoch 6/25
75/75 [==============================] - 8s 111ms/step - loss: 0.2107 - accurac
y: 0.9229
Epoch 7/25
75/75 [==============================] - 8s 112ms/step - loss: 0.1843 - accurac
y: 0.9320
Epoch 8/25
75/75 [==============================] - 8s 110ms/step - loss: 0.1260 - accurac
y: 0.9542
Epoch 9/25
75/75 [==============================] - 8s 110ms/step - loss: 0.0978 - accurac
y: 0.9651
Epoch 10/25
75/75 [==============================] - 8s 112ms/step - loss: 0.1328 - accurac
y: 0.9532
Epoch 11/25
75/75 [==============================] - 8s 111ms/step - loss: 0.0884 - accurac
y: 0.9694
Epoch 12/25
75/75 [==============================] - 8s 111ms/step - loss: 0.0989 - accurac
y: 0.9659
Epoch 13/25
75/75 [==============================] - 8s 111ms/step - loss: 0.0680 - accurac
y: 0.9770
Epoch 14/25
75/75 [==============================] - 8s 111ms/step - loss: 0.0431 - accurac
y: 0.9856
Epoch 15/25
75/75 [==============================] - 8s 111ms/step - loss: 0.0657 - accurac
y: 0.9774
Epoch 16/25
75/75 [==============================] - 8s 111ms/step - loss: 0.0592 - accurac
y: 0.9797
Epoch 17/25
75/75 [==============================] - 8s 110ms/step - loss: 0.0499 - accurac
```

```
y: 0.9832
Epoch 18/25
75/75 [==============================] - 8s 111ms/step - loss: 0.0746 - accurac
y: 0.9751
Epoch 19/25
75/75 [==============================] - 8s 111ms/step - loss: 0.0408 - accurac
y: 0.9868
Epoch 20/25
75/75 [==============================] - 8s 112ms/step - loss: 0.0174 - accurac
y: 0.9946
Epoch 21/25
75/75 [==============================] - 8s 113ms/step - loss: 0.0170 - accurac
y: 0.9940
Epoch 22/25
75/75 [==============================] - 8s 111ms/step - loss: 0.0419 - accurac
y: 0.9861
Epoch 23/25
75/75 [==============================] - 8s 112ms/step - loss: 0.0772 - accurac
y: 0.9748
Epoch 24/25
75/75 [==============================] - 8s 112ms/step - loss: 0.0281 - accurac
y: 0.9908
Epoch 25/25
75/75 [==============================] - 8s 112ms/step - loss: 0.0092 - accurac
y: 0.9975
```

In [45]:
```
accuracy = model.evaluate(x_test, y_test, verbose=1)[1]
print("Test: accuracy = ",accuracy*100,"%")
```

```
387/387 [==============================] - 10s 25ms/step - loss: 0.1155 - accur
acy: 0.9757
Test: accuracy =  97.56866097450256 %
```

CNN

In [21]:
```
x_train = x_train.reshape(x_train.shape[0], 125,100,3)
x_test = x_test.reshape(x_test.shape[0], 125, 100, 3)
print(x_train.shape)
print(x_test.shape)
```

```
(37137, 125, 100, 3)
(12380, 125, 100, 3)
```

In [32]:
```
input_shape = (125, 100, 3)
num_classes = 7

model = Sequential()
model.add(Conv2D(64, kernel_size=(3, 3),activation='relu',padding = 'Same',input_
model.add(Conv2D(64,kernel_size=(3, 3), activation='relu',padding = 'Same'))
model.add(MaxPooling2D(pool_size = (2, 2)))
model.add(Dropout(0.16))

model.add(Conv2D(128, (3, 3), activation='relu',padding = 'same'))
model.add(Conv2D(128, (3, 3), activation='relu',padding = 'Same'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.20))

model.add(Flatten())
model.add(Dense(512, activation='relu'))
model.add(Dense(256, activation='relu'))
model.add(Dropout(0.3))
model.add(Dense(num_classes, activation='softmax'))
model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 conv2d_4 (Conv2D)           (None, 125, 100, 64)      1792      
                                                                 
 conv2d_5 (Conv2D)           (None, 125, 100, 64)      36928     
                                                                 
 max_pooling2d_2 (MaxPooling  (None, 62, 50, 64)       0         
 2D)                                                             
                                                                 
 dropout_3 (Dropout)         (None, 62, 50, 64)        0         
                                                                 
 conv2d_6 (Conv2D)           (None, 62, 50, 128)       73856     
                                                                 
 conv2d_7 (Conv2D)           (None, 62, 50, 128)       147584    
                                                                 
 max_pooling2d_3 (MaxPooling  (None, 31, 25, 128)      0         
 2D)                                                             
                                                                 
 dropout_4 (Dropout)         (None, 31, 25, 128)       0         
                                                                 
 flatten_1 (Flatten)         (None, 99200)             0         
                                                                 
 dense_3 (Dense)             (None, 512)               50790912  
                                                                 
 dense_4 (Dense)             (None, 256)               131328    
                                                                 
 dropout_5 (Dropout)         (None, 256)               0         
                                                                 
 dense_5 (Dense)             (None, 7)                 1799      
                                                                 
=================================================================
Total params: 51,184,199
Trainable params: 51,184,199
```

```
Non-trainable params: 0
_________________________________________________________________
```

In [33]:
```
model.compile(optimizer= "Adam",
             loss='categorical_crossentropy',
             metrics=['accuracy'])

learning_rate_reduction = ReduceLROnPlateau(monitor='val_accuracy',
                                            patience=4,
                                            verbose=1,
                                            factor=0.5,
                                            min_lr=0.00001)
```

In [34]:
```
#x_train, x_validate, y_train, y_validate = train_test_split(x_train, y_train, te


# Reshape image in 3 dimensions (height = 100, width = 125 , canal = 3)
x_train = x_train.reshape(x_train.shape[0], *(125, 100, 3))
x_test = x_test.reshape(x_test.shape[0], *(125, 100, 3))
#x_validate = x_validate.reshape(x_validate.shape[0], *(100, 125, 3))

tf.config.run_functions_eagerly(True)


model.fit(x_train, y_train, batch_size = 500, epochs = 10)
```

```
Epoch 1/10
75/75 [==============================] - 2494s 33s/step - loss: 1.9435 - accura
cy: 0.3221
Epoch 2/10
75/75 [==============================] - 2491s 33s/step - loss: 1.1120 - accura
cy: 0.5682
Epoch 3/10
75/75 [==============================] - 2481s 33s/step - loss: 0.6452 - accura
cy: 0.7605
Epoch 4/10
75/75 [==============================] - 2484s 33s/step - loss: 0.3469 - accura
cy: 0.8690
Epoch 5/10
75/75 [==============================] - 2483s 33s/step - loss: 0.2107 - accura
cy: 0.9219
Epoch 6/10
75/75 [==============================] - 2463s 33s/step - loss: 0.1386 - accura
cy: 0.9510
Epoch 7/10
75/75 [==============================] - 2462s 33s/step - loss: 0.0884 - accura
cy: 0.9690
Epoch 8/10
75/75 [==============================] - 2460s 33s/step - loss: 0.0597 - accura
cy: 0.9794
Epoch 9/10
75/75 [==============================] - 2467s 33s/step - loss: 0.0521 - accura
cy: 0.9823
Epoch 10/10
75/75 [==============================] - 2452s 33s/step - loss: 0.0357 - accura
cy: 0.9881
```

Out[34]:
```
<keras.callbacks.History at 0x2a0b3f25850>
```

In [35]:
```
test_loss, test_acc = model.evaluate(x_test, y_test)
print("Test Accuracy: ",test_acc*100,"%")
```

```
387/387 [==============================] - 207s 534ms/step - loss: 0.1155 - acc
uracy: 0.9727
Test Accuracy:  97.2697913646698 %
```

In [ ]:

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