```
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 [1]: 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
(D 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
1	8 HAM_0005132	ISIC_0025837	bkl	histo	70.0	female	back
,	9 HAM_0005132	ISIC_0025209	bkl	histo	70.0	female	back

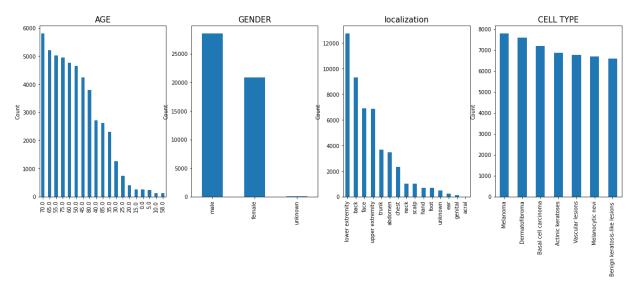
```
In [3]: df.isnull().sum()
```

In [4]: df.count()

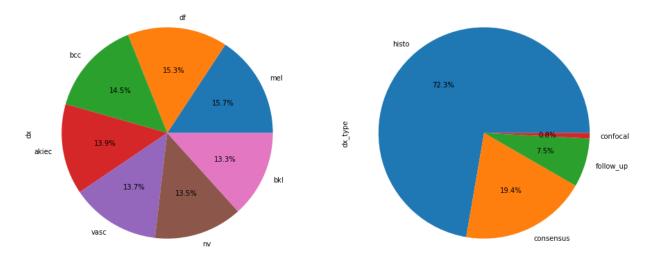
```
In [5]: | df['age'].fillna(int(df['age'].mean()),inplace=True)
        df.isnull().sum()
Out[5]: lesion id
         image id
                          0
                          0
         dx
         dx_type
                          0
         age
                          0
                          0
         sex
         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]:
                                                       sex localization
                lesion_id
                             image_id dx dx_type
                                                  age
            HAM 0000118 ISIC 0027419 bkl
                                            histo 80.0
                                                      male
                                                                 scalp skinCancer\HAM10000 images
            HAM 0000118 ISIC 0025030 bkl
                                            histo 80.0 male
                                                                 scalp skinCancer\HAM10000 images
         2 HAM_0002730 ISIC_0026769 bkl
                                            histo 80.0 male
                                                                      skinCancer\HAM10000_images_
         3 HAM 0002730 ISIC 0025661 bkl
                                            histo 80.0 male
                                                                      skinCancer\HAM10000 images
                                                                 scalp
         4 HAM 0001466 ISIC 0031633 bkl
                                            histo 75.0 male
                                                                      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
                                                         scalp skinCancer\HAM10000_images_part_1\ISIC_002
                                  histo 80.0 male
           2 HAM 0002730 bkl
                                                         scalp skinCancer\HAM10000 images part 1\ISIC 002
                                  histo 80.0 male
           3 HAM_0002730 bkl
                                  histo 80.0 male
                                                         scalp skinCancer\HAM10000_images_part_1\ISIC_002
           4 HAM_0001466 bkl
                                  histo 75.0 male
                                                              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, test
         tf.unique(x train o.cell type.values)
Out[12]: Unique(y=<tf.Tensor: shape=(7,), dtype=string, numpy=</pre>
         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 \text{ test} = (x \text{ test} - x \text{ test mean})/x \text{ 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., \ldots, 0., 0., 0.]
                 [0., 0., 0., \ldots, 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., \ldots, 0., 0., 0.]
                 [0., 1., 0., ..., 0., 0., 0.]
                 [0., 1., 0., \ldots, 0., 0., 0.]
                 [0., 1., 0., \ldots, 0., 0., 0.]
                 [0., 0., 0., ..., 0., 0., 1.]], dtype=float32)
```

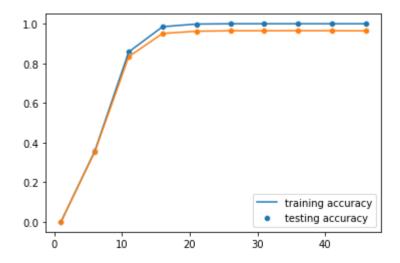
```
In [17]: y test o.value counts()
Out[17]: 5
               1924
               1907
          3
          1
               1750
          0
               1730
               1697
          6
          2
               1689
               1683
          Name: cell_type_idx, dtype: int64
In [18]: # 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 \text{ test} = x \text{ test.reshape}(x \text{ test o.shape}[0], *(100, 125, 3))
In [19]: x \text{ train} = x \text{ train.reshape}(x \text{ train.shape}[0],125*100*3)
          x_{\text{test}} = x_{\text{test.reshape}}(x_{\text{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
            -0.2329963811
```

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:</pre>
                  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'])
```

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



```
print('This is the best depth for Decision Tree Classifier: ', best depth, '\nAcc
In [25]:
         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:
         Accuracy score is: 0.9651050080775444
         Confusion Matrix:
           [[1702
                     0
                          7
                                0
                                    21
                                               0]
                               0
                                              3]
               0 1736
                         0
                                   11
                                         0
                    0 1689
                               0
                                         0
                                              0]
               0
                         0 1907
                                              01
              22
                   41
                       126
                               7 1284
                                       176
                                             27]
               0
                                    0 1922
                    0
                         2
                                              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
                                                  0.99
                                        1.00
                                                             1697
                                                  0.96
                                                            12380
              accuracy
                             0.97
                                        0.96
                                                  0.96
                                                            12380
             macro avg
```

Random Forest

0.97

0.96

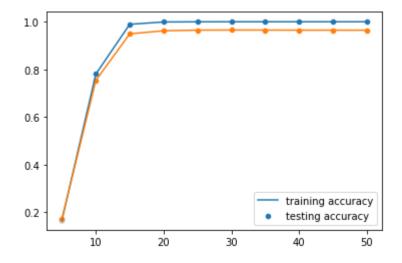
0.96

12380

weighted avg

```
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:</pre>
                  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
```

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 1689
                               0
                                              0]
               0
                    0
                         0 1907
                                    0
                                              0]
             398
                    3
                        15
                               0 1245
                                        22
                                              0]
               0
                    0
                         0
                               0
                                    0 1924
                                              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
                              0.97
                                        0.96
             macro avg
                                                   0.96
                                                            12380
          weighted avg
                              0.97
                                        0.96
                                                   0.96
                                                            12380
```

KNN

```
In [*]: k = range(1,102,3)
        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:</pre>
                 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'])
```

```
In [*]: 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)
```

In [*]: x_train.shape

MLP

```
In [ ]: # define the keras model
model = Sequential()

model.add(Dense(units= 64, kernel_initializer = 'uniform', activation = 'relu', i
model.add(Dense(units= 128, kernel_initializer = 'uniform', activation = 'relu'))
model.add(Dense(units= 64, kernel_initializer = 'uniform', activation = 'relu'))
model.add(Dense(units= 32, kernel_initializer = 'uniform', activation = 'relu'))
model.add(Dense(units= 7, kernel_initializer = 'uniform', activation = 'softmax'
model.summary()
```

```
In []: # 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 = 20, epochs = 25)
In []: accuracy = model.evaluate(x_test, y_test, verbose=1)[1]
    print("Test: accuracy = ",accuracy*100,"%")
```

CNN

```
In [ ]: |x_train = x_train.reshape(x_train.shape[0], 125,100,3)
        x_{\text{test}} = x_{\text{test.reshape}}(x_{\text{test.shape}}[0], 125, 100, 3)
        print(x train.shape)
        print(x test.shape)
In [ ]: |input_shape = (125, 100, 3)
        num classes = 7
        model = Sequential()
        model.add(Conv2D(32, kernel_size=(3, 3),activation='relu',padding = 'Same',input]
        model.add(Conv2D(32,kernel_size=(3, 3), activation='relu',padding = 'Same'))
        model.add(MaxPooling2D(pool size = (2, 2)))
        model.add(Dropout(0.16))
        model.add(Conv2D(64, (3, 3), activation='relu',padding = 'same'))
        model.add(Conv2D(64, (3, 3), activation='relu',padding = 'Same'))
        model.add(MaxPooling2D(pool size=(2, 2)))
        model.add(Dropout(0.20))
        model.add(Flatten())
        model.add(Dense(256, activation='relu'))
        model.add(Dense(128, activation='relu'))
        model.add(Dropout(0.3))
        model.add(Dense(num classes, activation='softmax'))
        model.summary()
```

```
In [ ]: #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], *(100, 125, 3))
         x_{\text{test}} = x_{\text{test.reshape}}(x_{\text{test.shape}}[0], *(100, 125, 3))
         \#x validate = x validate.reshape(x validate.shape[0], *(100, 125, 3))
         model.fit(x_train, y_train, batch_size = 100, epochs = 20)
In [ ]: test_loss, test_acc = model.evaluate(x_test, y_test)
         print("Test Accuracy: ",test_acc*100,"%")
In [ ]:
```