Dataset Overview

HAM10000 ("Human Against Machine with 10000 training images") dataset - a large collection of multi-source dermatoscopic images of pigmented lesions

The dermatoscopic images are collected from different populations, acquired and stored by different modalities. The final dataset consists of 10015 dermatoscopic images.

It has 7 different classes of skin cancer which are listed below :

- **Melanocytic nevi**
- **Melanoma**
- **Benign keratosis-like lesions**
- **Basal cell carcinoma**
- **Actinic keratoses**
- **Vascular lesions**
- **Dermatofibroma**

Importing libraries

In [45]:

```
import seaborn as sns
import pandas as pd
import matplotlib.pyplot as plt
from imblearn.over_sampling import RandomOverSampler
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score,KFold

import os, cv2
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, Flatten, Dense, MaxPool2D, Activation, Batch
Normalization
from sklearn.metrics import classification_report, accuracy_score
```

Reading the Data

In [46]:

```
data = pd.read_csv('/kaggle/input/skin-cancer-mnist-ham10000/hmnist_28_28_RGB.csv')
data.head()
```

Out[46]:

	pixel0000	pixel0001	pixel0002	pixel0003	pixel0004	pixel0005	pixel0006	pixel0007	pixel0008	pixel0009	...	pixel2343	pix
0	192	153	193	195	155	192	197	154	185	202	...	173	
1	25	14	30	68	48	75	123	93	126	158	...	60	
2	192	138	153	200	145	163	201	142	160	206	...	167	
3	38	19	30	95	59	72	143	103	119	171	...	44	
4	158	113	139	194	144	174	215	162	191	225	...	209	

5 rows × 2353 columns

Data Preprocessing

Data Preprocessing

Data Cleaning

In [47]:

```
data['label'].unique()
y = data['label']
x = data.drop(columns = ['label'])
data.isnull().sum().sum()  #no null values present
```

Out[47]:

```
0
```

In [48]:

```
meta_data = pd.read_csv('/kaggle/input/skin-cancer-mnist-ham10000/HAM10000_metadata.csv')
meta_data.head()
```

Out[48]:

	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

In [49]:

```
meta_data['dx'].unique()
```

Out[49]:

```
array(['bkl', 'nv', 'df', 'mel', 'vasc', 'bcc', 'akiec'], dtype=object)
```

In [50]:

```
data.isnull().sum().sum()  #no null values present
meta_data.head()
```

Out[50]:

	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

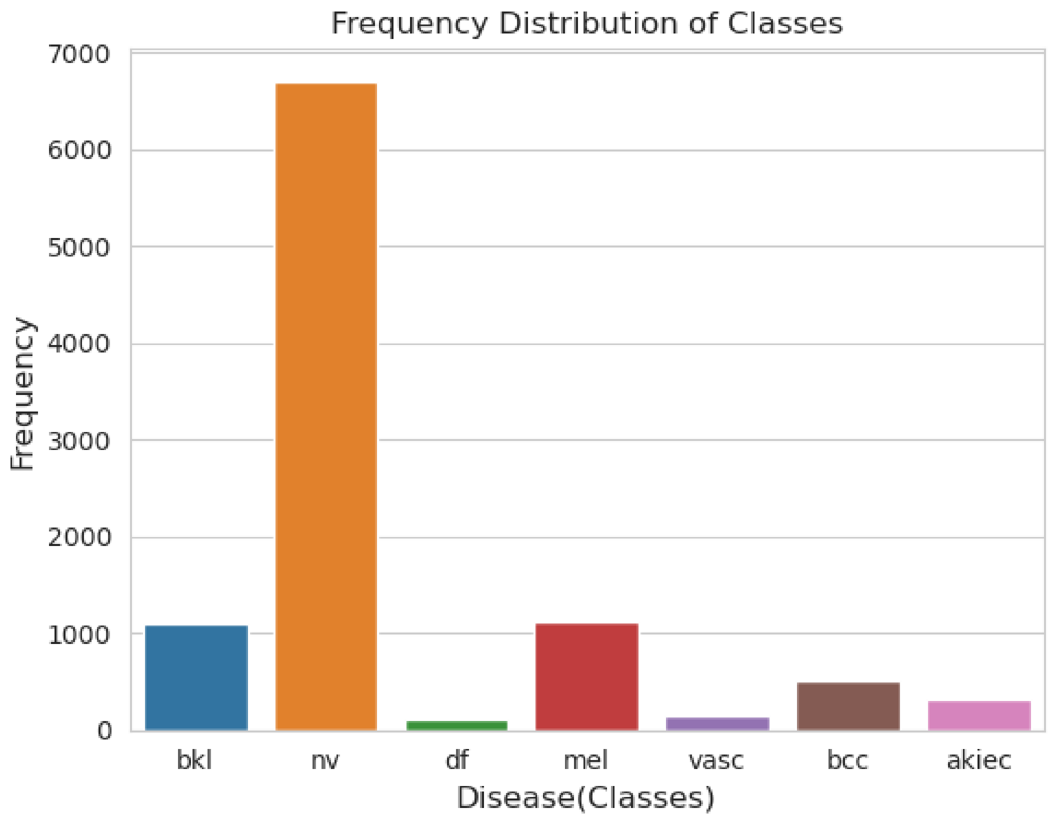
Exploratory Data Analysis

In [51]:

```
sns.countplot(x = 'dx', data = meta_data)
plt.xlabel('Disease(Classes)', size=12)
plt.ylabel('Frequency', size=12)
plt.title('Frequency Distribution of Classes')
```

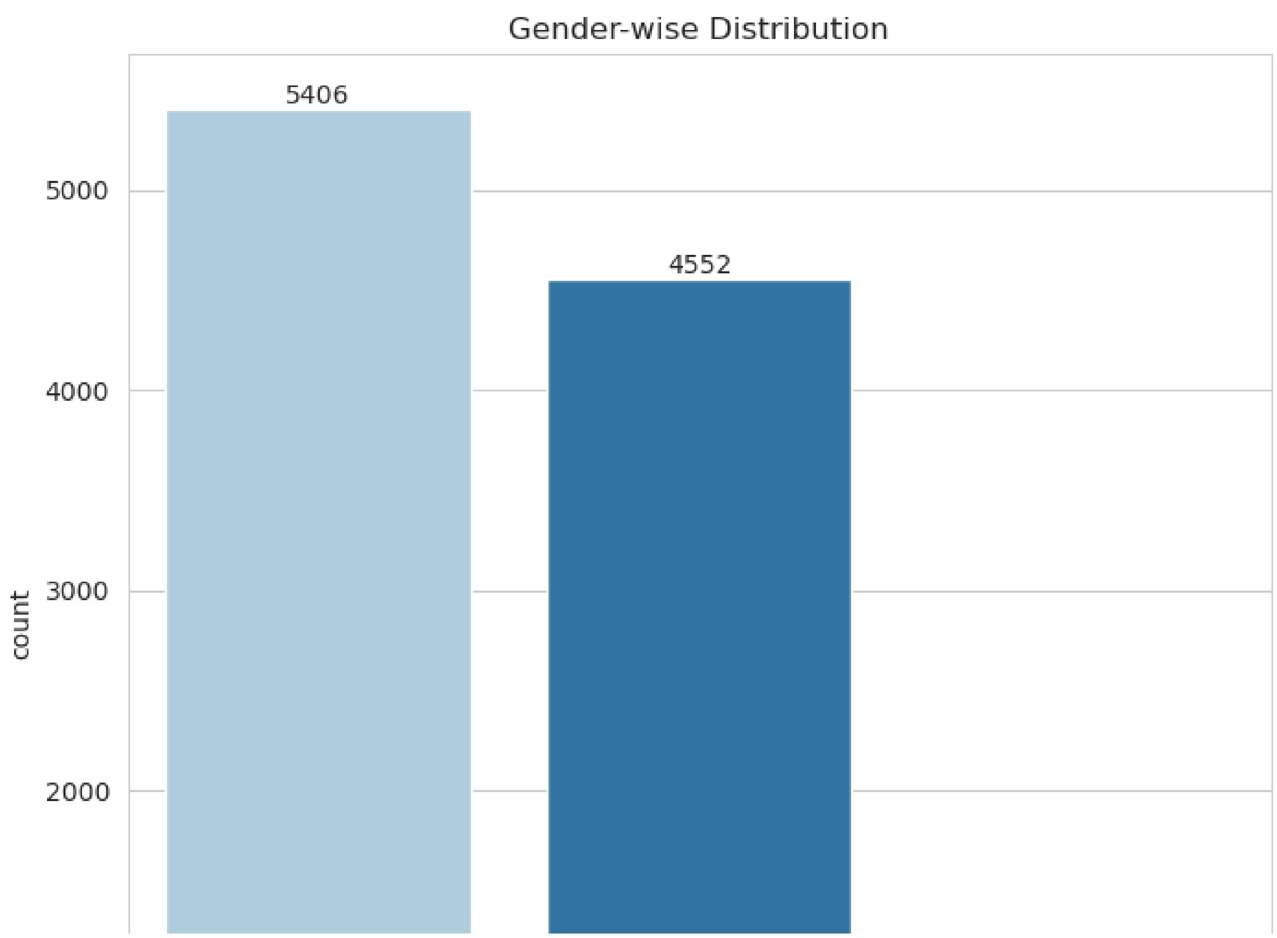
Out[51]:

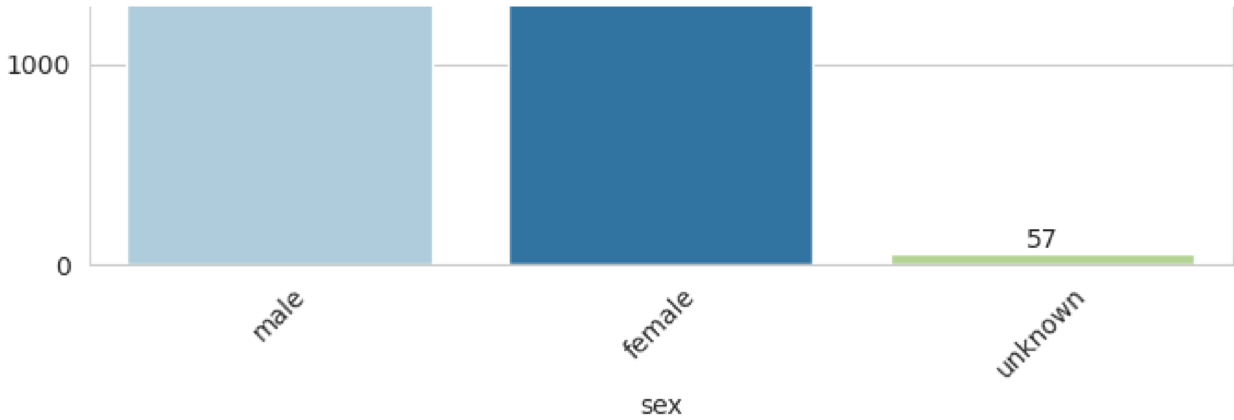
```
Text(0.5, 1.0, 'Frequency Distribution of Classes')
```



In [52]:

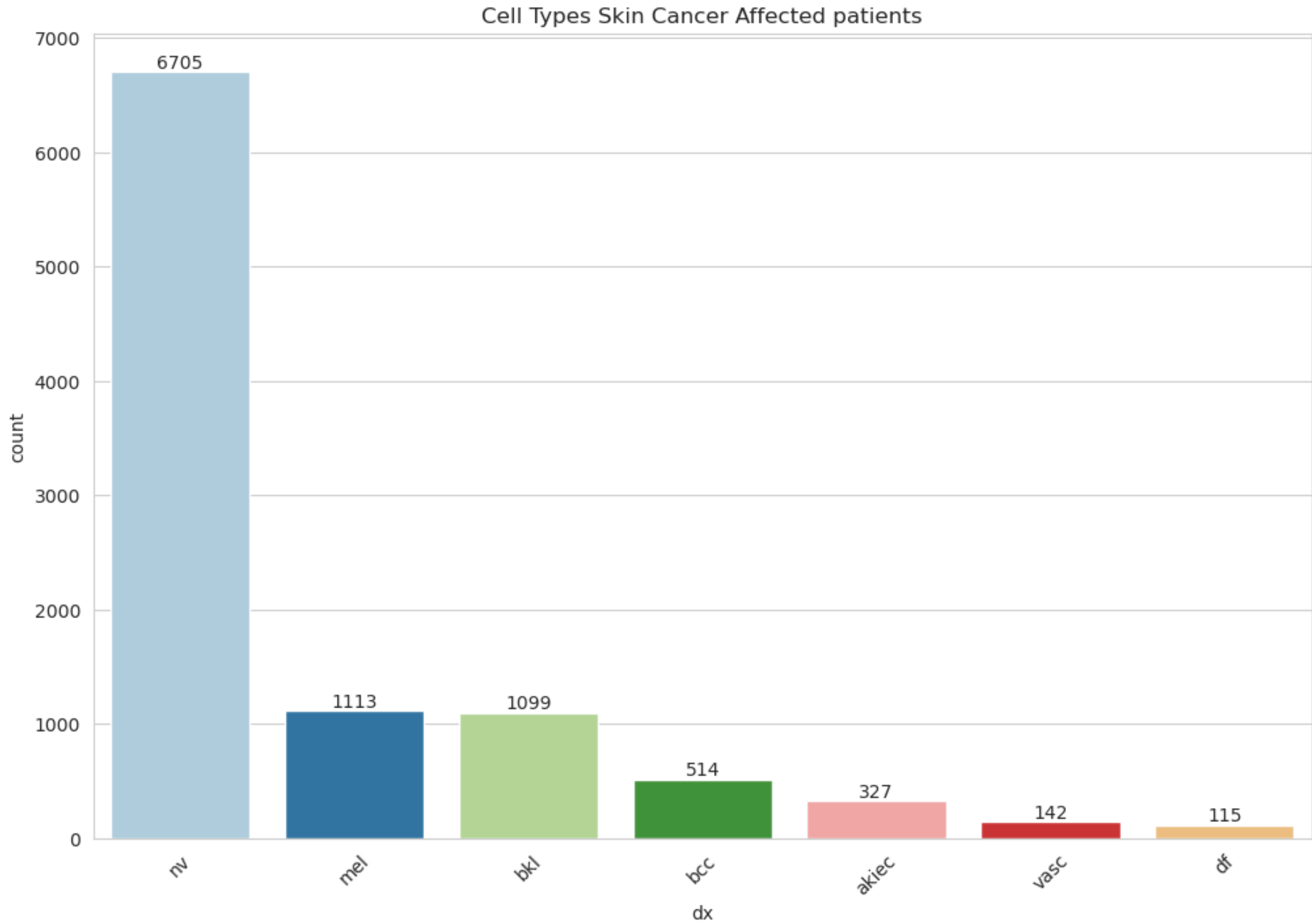
```
sns.set_style('whitegrid')
colors = ['#87ace8','#e3784d', 'green']
fig,axes = plt.subplots(figsize=(8,8))

ax = sns.countplot(x='sex',data=meta_data, palette = 'Paired')
for container in ax.containers:
    ax.bar_label(container)
plt.title('Gender-wise Distribution')
plt.xticks(rotation=45)
plt.show()
```





In [53]:

```
sns.set_style('whitegrid')
fig,axes = plt.subplots(figsize=(12,8))
ax = sns.countplot(x='dx',data=meta_data, order = meta_data['dx'].value_counts().index,
palette = 'Paired')
for container in ax.containers:
    ax.bar_label(container)
plt.title('Cell Types Skin Cancer Affected patients')
plt.xticks(rotation=45)
plt.show()
```



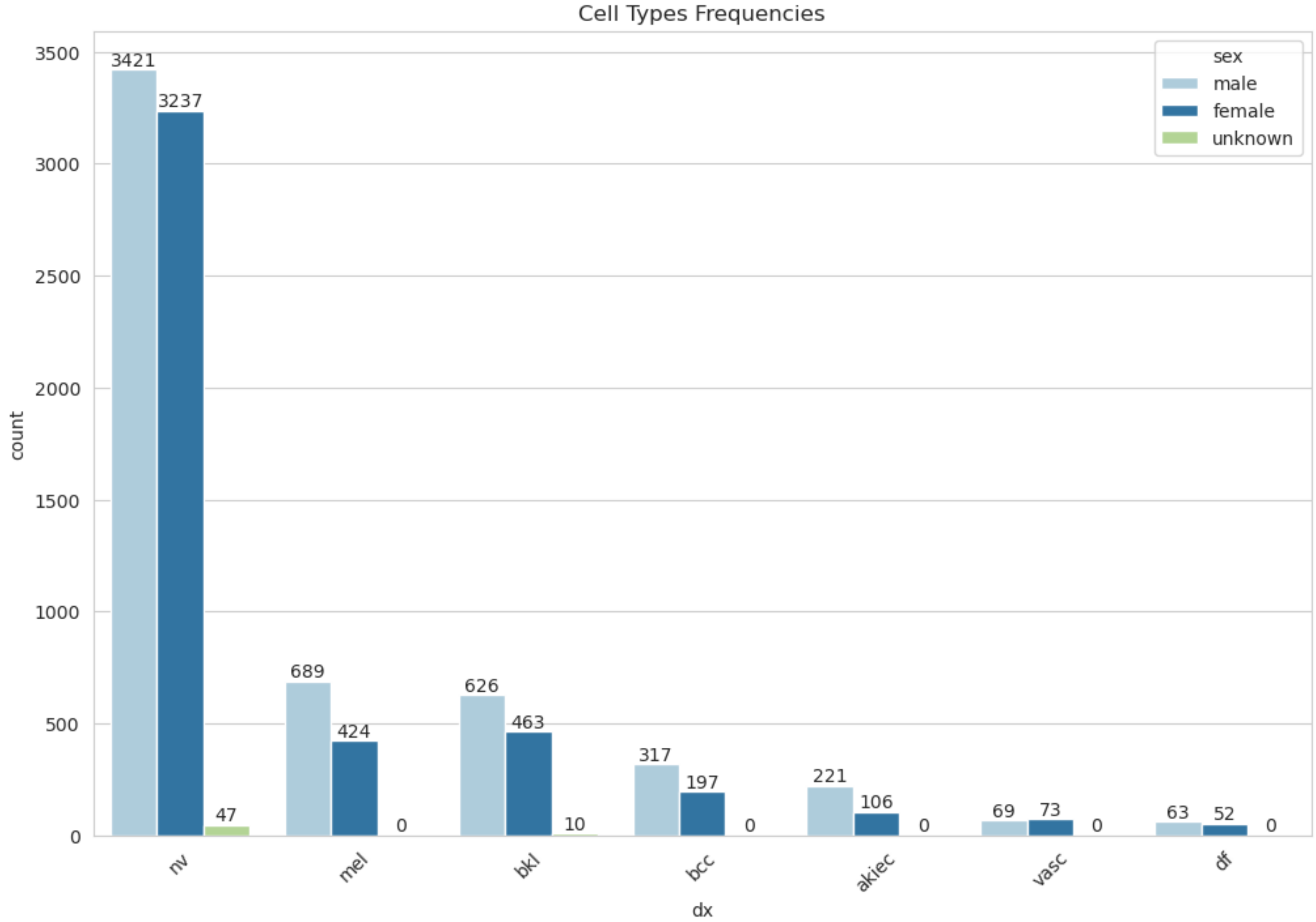
In [54]:

```
classes = {2:'bkl', 4:'nv', 3:'df', 6:'mel', 5:'vasc', 1:'bcc', 0:'akiec'}

classes_labels=[]
for key in classes.keys():
    classes_labels.append(key)
print(classes_labels)
```

```
[2, 4, 3, 6, 5, 1, 0]
```

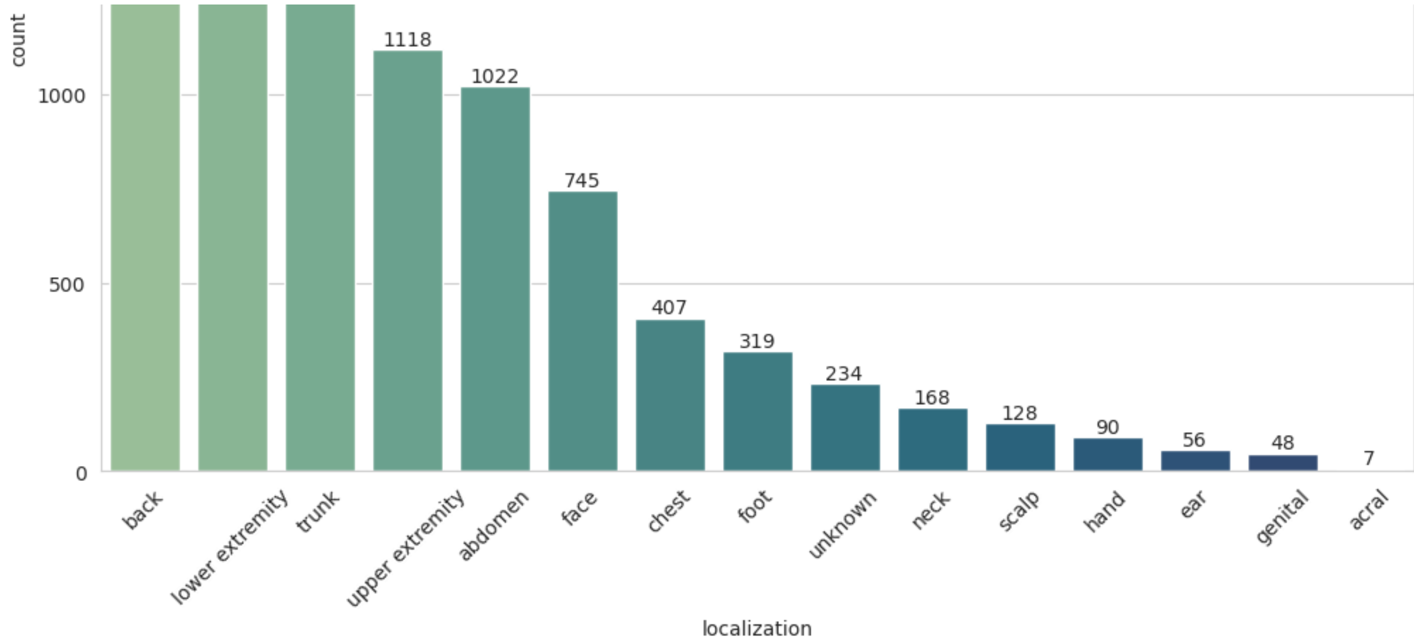
In [55]:

```
sns.set_style('whitegrid')
fig,axes = plt.subplots(figsize=(12,8))
ax = sns.countplot(x='dx',hue='sex', data=meta_data, order = meta_data['dx'].value_count
s().index, palette = 'Paired')
for container in ax.containers:
    ax.bar_label(container)
plt.title('Cell Types Frequencies')
plt.xticks(rotation=45)
plt.show()
```



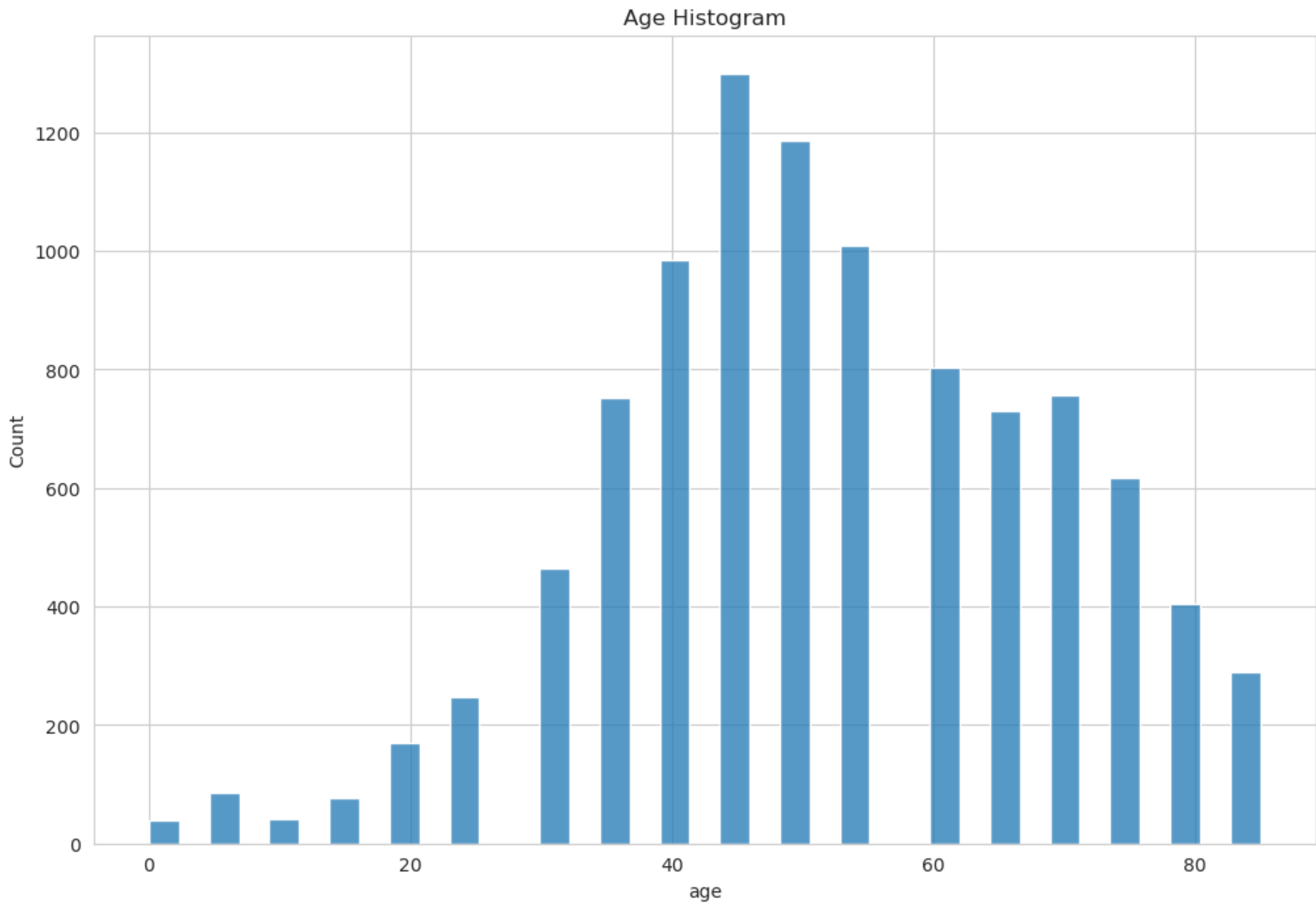
In [56]:

```
sns.set_style('whitegrid')
fig,axes = plt.subplots(figsize=(12,8))
ax = sns.countplot(x='localization',data=meta_data, order = meta_data['localization'].val
ue_counts().index, palette = 'crest')
for container in ax.containers:
    ax.bar_label(container)
plt.title('Localization Area Frequencies')
plt.xticks(rotation=45)
plt.show()
```



In [57]:

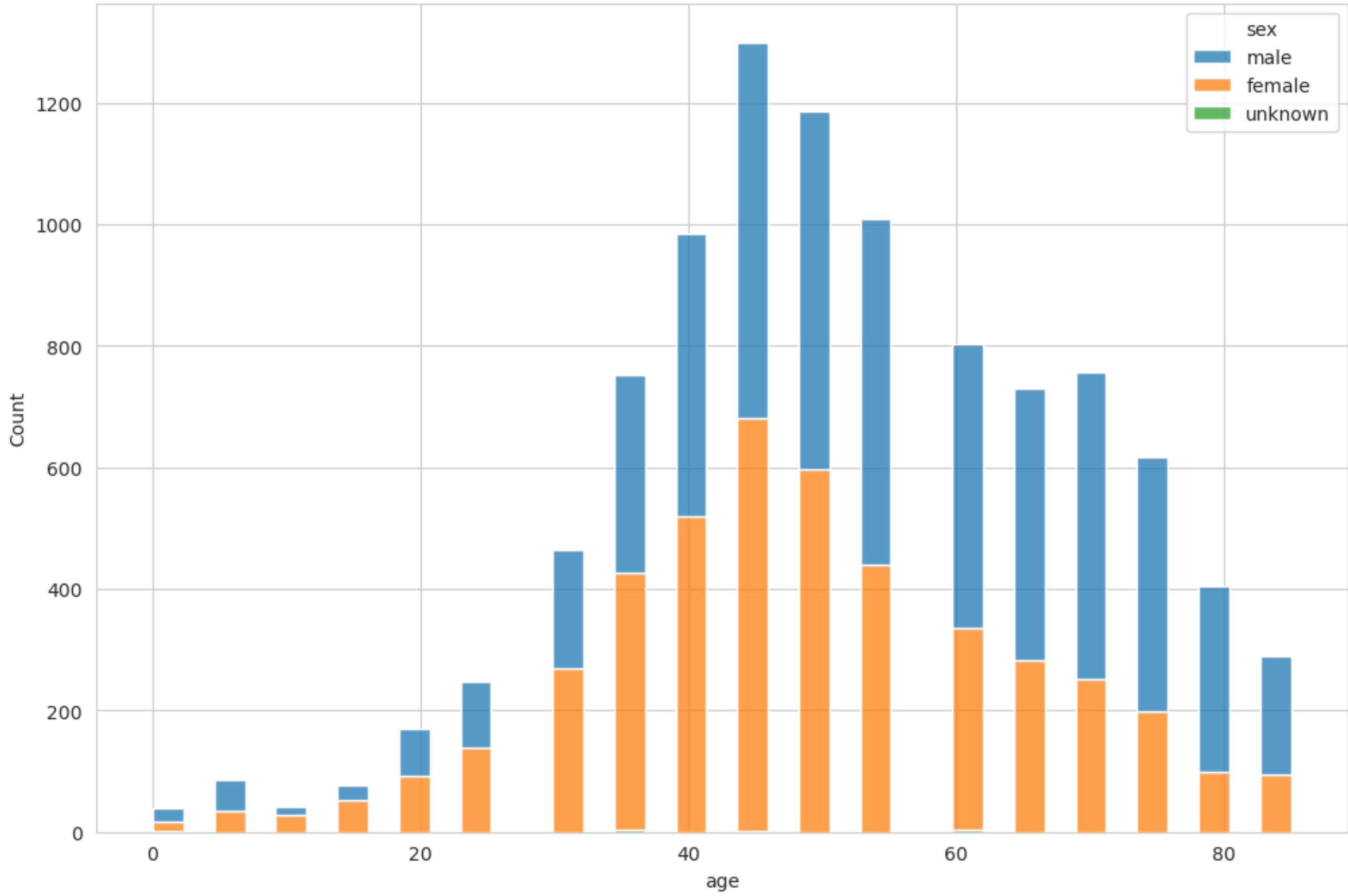
```
sns.set_style('whitegrid')
fig,axes = plt.subplots(figsize=(12,8))
ax = sns.histplot(data=meta_data, x='age')
plt.title('Age Histogram')
plt.show()
```



In [58]:

```
sns.set_style('whitegrid')
fig,axes = plt.subplots(figsize=(12,8))
ax = sns.histplot(data=meta_data, x='age',hue='sex',multiple='stack')
plt.title('Age Histogram Gender Wise')
plt.show()
```

Age Histogram Gender Wise



In [59]:

```
print(x.shape,y.shape)
# To overcome class imbalace
oversample = RandomOverSampler()
x,y  = oversample.fit_resample(x,y)
print(x.shape,y.shape)
```

```
(10015, 2352) (10015,)
(46935, 2352) (46935,)
```

In [60]:

```
# reshaping the data so that it can be taken by convolution neural network(without distur
bing the no. of samples)
x = np.array(x).reshape(-1,28,28,3)
print('Shape of X :',x.shape)
print('Shape of y :',y.shape)
```

```
Shape of X : (46935, 28, 28, 3)
Shape of y : (46935,)
```

In [61]:

```
# Splitting Data
X_train, X_test, Y_train, Y_test = train_test_split(x,y, test_size=0.2, random_state=1)
print(X_train.shape,Y_train.shape)
print(X_test.shape , Y_test.shape)
```

```
(37548, 28, 28, 3) (37548,)
(9387, 28, 28, 3) (9387,)
```

In [62]:

```
model_CNN = Sequential()
model_CNN.add(Conv2D(32, kernel_size = (3,3), input_shape = (28, 28, 3), activation = 'r
elu', padding = 'same'))
model_CNN.add(BatchNormalization())
```

```
model_CNN.add(MaxPool2D(pool_size = (2,2)))


model_CNN.add(Conv2D(64, kernel_size = (3,3), activation = 'relu', padding = 'same'))
model_CNN.add(BatchNormalization())

model_CNN.add(MaxPool2D(pool_size = (2,2), padding = 'same'))
model_CNN.add(Conv2D(128, kernel_size = (3,3), activation = 'relu', padding = 'same'))
model_CNN.add(BatchNormalization())

model_CNN.add(MaxPool2D(pool_size = (2,2), padding = 'same'))

model_CNN.add(Flatten())


model_CNN.add(Dense(64, activation = 'relu'))
model_CNN.add(BatchNormalization())


model_CNN.add(Dense(32))
model_CNN.add(Activation(activation='relu'))
model_CNN.add(BatchNormalization())

model_CNN.add(Dense(16))
model_CNN.add(Activation(activation='relu'))
model_CNN.add(BatchNormalization())

model_CNN.add(Dense(7))
model_CNN.add(Activation(activation='softmax'))

optimizer = tf.keras.optimizers.Adam(learning_rate = 0.001)

model_CNN.compile(loss = 'sparse_categorical_crossentropy',
                  optimizer = optimizer,
                   metrics = ['accuracy'])
print(model_CNN.summary())
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 conv2d_3 (Conv2D)           (None, 28, 28, 32)        896       
                                                                 
 batch_normalization_6 (Batc  (None, 28, 28, 32)       128       
 hNormalization)                                                 
                                                                 
 max_pooling2d_3 (MaxPooling  (None, 14, 14, 32)       0         
 2D)                                                             
                                                                 
 conv2d_4 (Conv2D)           (None, 14, 14, 64)        18496     
                                                                 
 batch_normalization_7 (Batc  (None, 14, 14, 64)       256       
 hNormalization)                                                 
                                                                 
 max_pooling2d_4 (MaxPooling  (None, 7, 7, 64)         0         
 2D)                                                             
                                                                 
 conv2d_5 (Conv2D)           (None, 7, 7, 128)         73856     
                                                                 
 batch_normalization_8 (Batc  (None, 7, 7, 128)        512       
 hNormalization)                                                 
                                                                 
 max_pooling2d_5 (MaxPooling  (None, 4, 4, 128)        0         
 2D)                                                             
                                                                 
 flatten_1 (Flatten)         (None, 2048)              0         
                                                                 
 dense_4 (Dense)             (None, 64)                131136    
                                                                 
 batch_normalization_9 (Batc  (None, 64)               256       
 hNormalization)                                                 
```

```
 dense_5 (Dense)             (None, 32)                2080

 activation_3 (Activation)   (None, 32)                0

 batch_normalization_10 (Bat  (None, 32)               128
 chNormalization)

 dense_6 (Dense)             (None, 16)                528

 activation_4 (Activation)   (None, 16)                0

 batch_normalization_11 (Bat  (None, 16)               64
 chNormalization)

 dense_7 (Dense)             (None, 7)                 119

 activation_5 (Activation)   (None, 7)                 0

=================================================================
Total params: 228,455
Trainable params: 227,783
Non-trainable params: 672
_________________________________________________________________
None
```

In [63]:

```
from tensorflow.keras.callbacks import ReduceLROnPlateau, EarlyStopping
early_stop = EarlyStopping(monitor='val_loss', patience=10, verbose=1, mode='auto')
reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=0.1, patience=3, verbose=1, mod
e='auto')
history = model_CNN.fit(X_train,
                    Y_train,
                    validation_split=0.2,
                    batch_size = 64,
                    epochs = 50,
                    callbacks = [reduce_lr, early_stop])
```

```
Epoch 1/50
470/470 [==============================] - 8s 9ms/step - loss: 0.9652 - accuracy: 0.6624
- val_loss: 0.7836 - val_accuracy: 0.7146 - lr: 0.0010
Epoch 2/50
470/470 [==============================] - 4s 8ms/step - loss: 0.4778 - accuracy: 0.8336
- val_loss: 0.8779 - val_accuracy: 0.6887 - lr: 0.0010
Epoch 3/50
470/470 [==============================] - 4s 8ms/step - loss: 0.2847 - accuracy: 0.8988
- val_loss: 0.5649 - val_accuracy: 0.7887 - lr: 0.0010
Epoch 4/50
470/470 [==============================] - 4s 8ms/step - loss: 0.2255 - accuracy: 0.9206
- val_loss: 0.4857 - val_accuracy: 0.8025 - lr: 0.0010
Epoch 5/50
470/470 [==============================] - 4s 9ms/step - loss: 0.1765 - accuracy: 0.9374
- val_loss: 0.7313 - val_accuracy: 0.7515 - lr: 0.0010
Epoch 6/50
470/470 [==============================] - 4s 9ms/step - loss: 0.1391 - accuracy: 0.9511
- val_loss: 0.3147 - val_accuracy: 0.8900 - lr: 0.0010
Epoch 7/50
470/470 [==============================] - 4s 8ms/step - loss: 0.1068 - accuracy: 0.9617
- val_loss: 0.2160 - val_accuracy: 0.9202 - lr: 0.0010
Epoch 8/50
470/470 [==============================] - 4s 8ms/step - loss: 0.1002 - accuracy: 0.9645
- val_loss: 0.2500 - val_accuracy: 0.9186 - lr: 0.0010
Epoch 9/50
470/470 [==============================] - 4s 8ms/step - loss: 0.0813 - accuracy: 0.9718
- val_loss: 0.2706 - val_accuracy: 0.9019 - lr: 0.0010
Epoch 10/50
468/470 [============================>.] - ETA: 0s - loss: 0.0711 - accuracy: 0.9743
Epoch 10: ReduceLROnPlateau reducing learning rate to 0.00010000000474974513.
470/470 [==============================] - 4s 8ms/step - loss: 0.0712 - accuracy: 0.9743
- val_loss: 0.2367 - val_accuracy: 0.9200 - lr: 0.0010
Epoch 11/50
```

```
470/470 [==============================] - 4s 8ms/step - loss: 0.0256 - accuracy: 0.9935
- val_loss: 0.0803 - val_accuracy: 0.9790 - lr: 1.0000e-04
Epoch 12/50
470/470 [==============================] - 4s 8ms/step - loss: 0.0143 - accuracy: 0.9972
- val_loss: 0.0699 - val_accuracy: 0.9815 - lr: 1.0000e-04
Epoch 13/50
470/470 [==============================] - 4s 8ms/step - loss: 0.0100 - accuracy: 0.9980
- val_loss: 0.0729 - val_accuracy: 0.9804 - lr: 1.0000e-04
Epoch 14/50
470/470 [==============================] - 4s 8ms/step - loss: 0.0076 - accuracy: 0.9987
- val_loss: 0.0745 - val_accuracy: 0.9799 - lr: 1.0000e-04
Epoch 15/50
463/470 [============================>.] - ETA: 0s - loss: 0.0059 - accuracy: 0.9992
Epoch 15: ReduceLROnPlateau reducing learning rate to 1.0000000474974514e-05.
470/470 [==============================] - 4s 8ms/step - loss: 0.0059 - accuracy: 0.9992
- val_loss: 0.0723 - val_accuracy: 0.9810 - lr: 1.0000e-04
Epoch 16/50
470/470 [==============================] - 4s 9ms/step - loss: 0.0046 - accuracy: 0.9995
- val_loss: 0.0743 - val_accuracy: 0.9802 - lr: 1.0000e-05
Epoch 17/50
470/470 [==============================] - 4s 7ms/step - loss: 0.0041 - accuracy: 0.9995
- val_loss: 0.0723 - val_accuracy: 0.9810 - lr: 1.0000e-05
Epoch 18/50
465/470 [============================>.] - ETA: 0s - loss: 0.0042 - accuracy: 0.9995
Epoch 18: ReduceLROnPlateau reducing learning rate to 1.0000000656873453e-06.
470/470 [==============================] - 4s 7ms/step - loss: 0.0043 - accuracy: 0.9995
- val_loss: 0.0705 - val_accuracy: 0.9816 - lr: 1.0000e-05
Epoch 19/50
470/470 [==============================] - 4s 9ms/step - loss: 0.0039 - accuracy: 0.9998
- val_loss: 0.0718 - val_accuracy: 0.9806 - lr: 1.0000e-06
Epoch 20/50
470/470 [==============================] - 4s 8ms/step - loss: 0.0038 - accuracy: 0.9997
- val_loss: 0.0710 - val_accuracy: 0.9810 - lr: 1.0000e-06
Epoch 21/50
464/470 [============================>.] - ETA: 0s - loss: 0.0039 - accuracy: 0.9997
Epoch 21: ReduceLROnPlateau reducing learning rate to 1.0000001111620805e-07.
470/470 [==============================] - 4s 8ms/step - loss: 0.0038 - accuracy: 0.9997
- val_loss: 0.0737 - val_accuracy: 0.9804 - lr: 1.0000e-06
Epoch 22/50
470/470 [==============================] - 5s 10ms/step - loss: 0.0037 - accuracy: 0.9998
- val_loss: 0.0713 - val_accuracy: 0.9814 - lr: 1.0000e-07
Epoch 22: early stopping
```

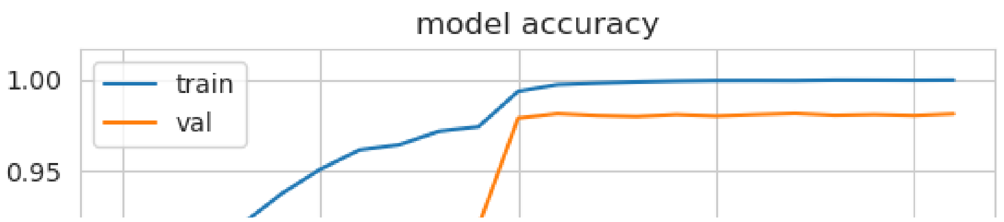
In [64]:

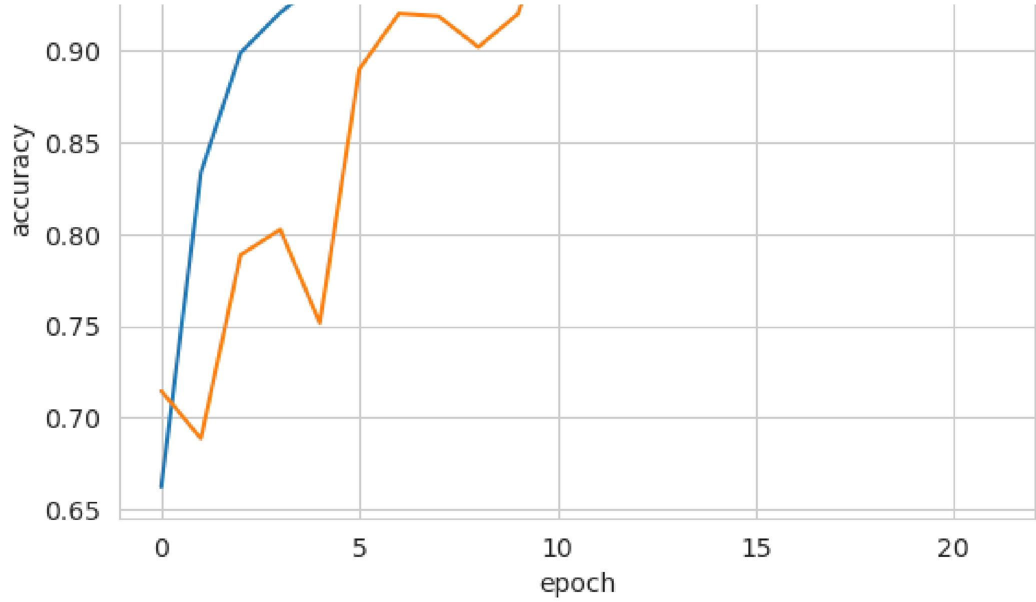
```
results = model_CNN.evaluate(X_test , Y_test, verbose=0)

print("CNN Model Test Results")
print("        Test Loss: {:.5f}".format(results[0]))
print("    Test Accuracy: {:.2f}%".format(results[1] * 100))
```

```
CNN Model Test Results
        Test Loss: 0.07409
    Test Accuracy: 98.02%
```

In [65]:

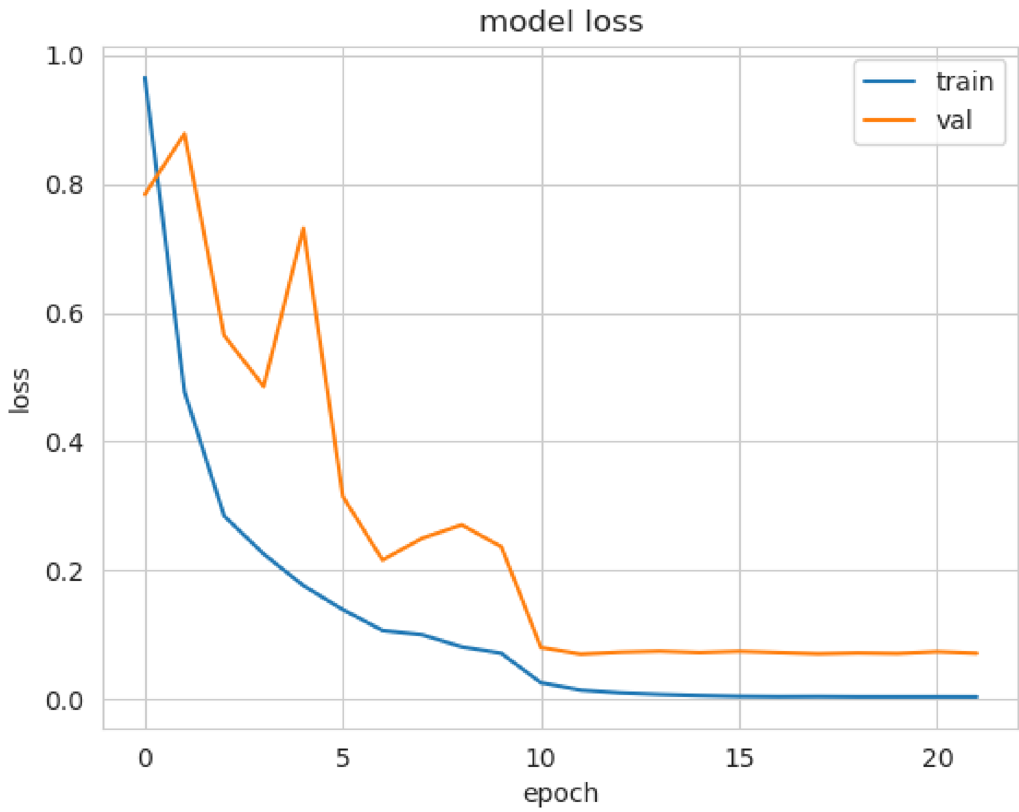
```
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'val'], loc='upper left')
plt.show()
```





In [66]:

```
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'val'], loc='upper right')
plt.show()
```



In [67]:

```
from sklearn.metrics import confusion_matrix , classification_report

y_true_CNN = list(Y_test)
y_pred_CNN = model_CNN.predict(X_test)
y_pred_CNN = list(map(lambda x: np.argmax(x), y_pred_CNN))
print("Predicting First Ten Rows:")
print('Y Actual Values :' , y_true_CNN[0:10])
print('Y Predicted Values :' , y_pred_CNN[0:10])
```

```
294/294 [==============================] - 1s 2ms/step
Predicting First Ten Rows:
```

```
Y Actual Values : [5, 1, 4, 0, 5, 0, 2, 0, 3, 2]
Y Predicted Values : [5, 1, 4, 0, 5, 0, 2, 0, 3, 2]
```

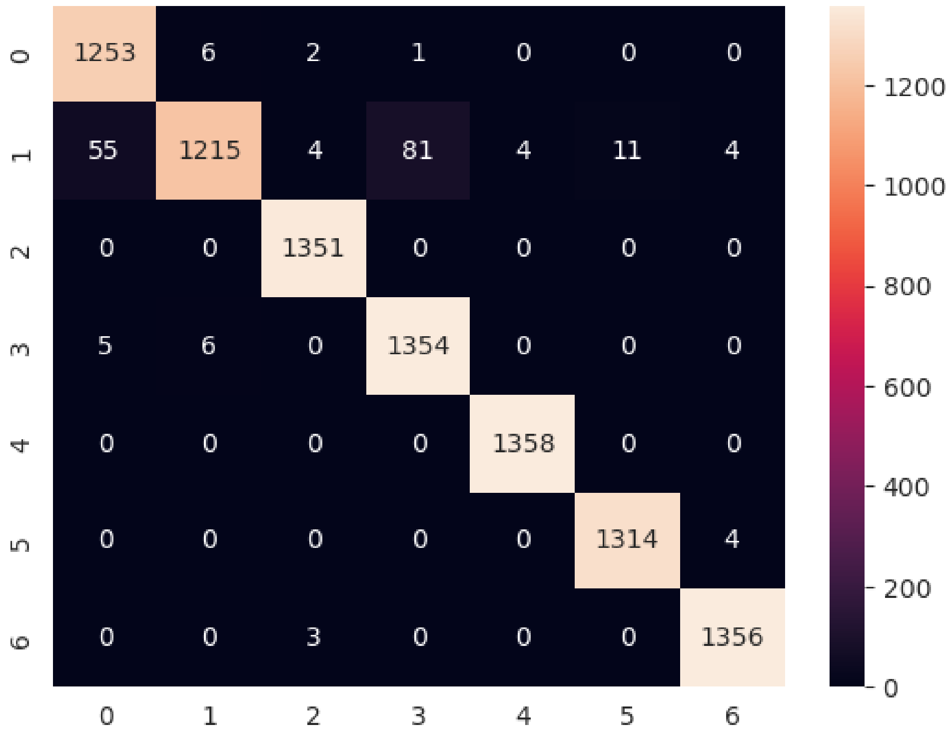
In [68]:

```python
cm_CNN = confusion_matrix(y_true_CNN,y_pred_CNN,labels=classes_labels)
print(confusion_matrix(y_true_CNN,y_pred_CNN,labels=classes_labels))
sns.heatmap(cm_CNN, annot = True, fmt='')
```

```
[[1253    6    2    1    0    0    0]
 [  55 1215    4   81    4   11    4]
 [   0    0 1351    0    0    0    0]
 [   5    6    0 1354    0    0    0]
 [   0    0    0    0 1358    0    0]
 [   0    0    0    0    0 1314    4]
 [   0    0    3    0    0    0 1356]]
```

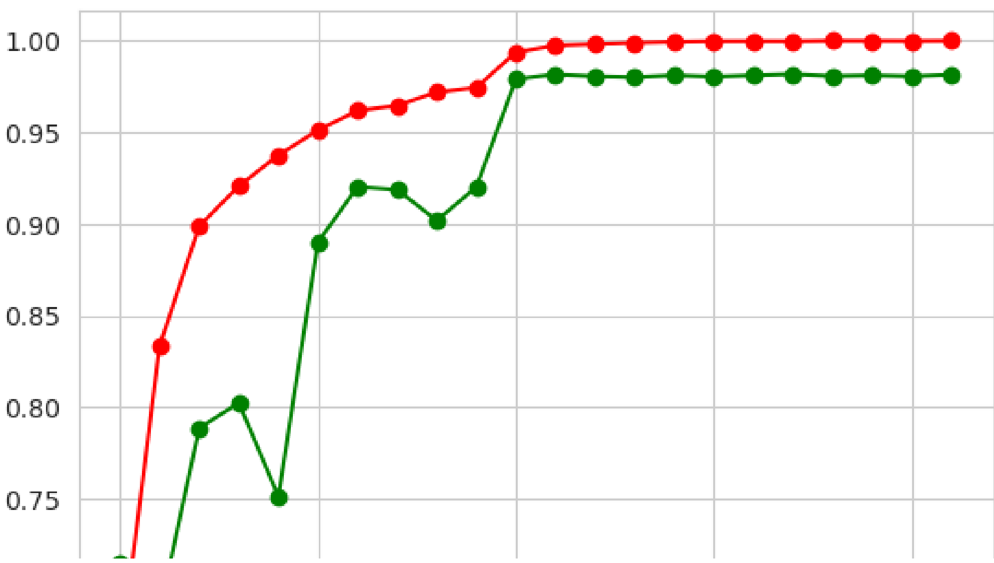
Out[68]:

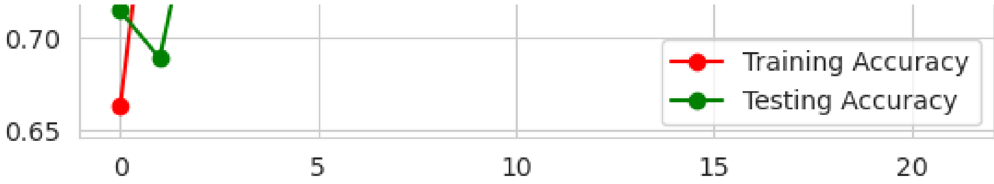
```
<AxesSubplot:>
```



In [69]:

```python
#training acc vs testing acc graph
plt.plot(history.history["accuracy"] , 'ro-' , label = "Training Accuracy")
plt.plot(history.history["val_accuracy"] , 'go-' , label = "Testing Accuracy")
plt.legend()
plt.show()
```





In [70]:

```
#predicting
y_pred_CNN  = model_CNN.predict(X_test)
target_names = [f"{classes[i]}" for i in range(7)]
y_pred_CNN = list(map(lambda x: np.argmax(x), y_pred_CNN))
print("CNN Model Prediction Results")
print(classification_report(Y_test , y_pred_CNN,target_names=target_names))
```

```
294/294 [==============================] - 1s 2ms/step
CNN Model Prediction Results
              precision    recall  f1-score   support

       akiec       0.99      1.00      1.00      1359
         bcc       0.99      1.00      0.99      1318
         bkl       0.95      0.99      0.97      1262
          df       0.99      1.00      1.00      1351
          nv       0.99      0.88      0.93      1374
        vasc       1.00      1.00      1.00      1358
         mel       0.94      0.99      0.97      1365

    accuracy                           0.98      9387
   macro avg       0.98      0.98      0.98      9387
weighted avg       0.98      0.98      0.98      9387
```

In [71]:

```
# Layers definitions
from keras import backend as K
for l in range(len(model_CNN.layers)):
    print(l, model_CNN.layers[l])
```

```
0 <keras.layers.convolutional.conv2d.Conv2D object at 0x7ff194bbf550>
1 <keras.layers.normalization.batch_normalization.BatchNormalization object at 0x7ff285e5
ef90>
2 <keras.layers.pooling.max_pooling2d.MaxPooling2D object at 0x7ff28631df50>
3 <keras.layers.convolutional.conv2d.Conv2D object at 0x7ff2668ddf50>
4 <keras.layers.normalization.batch_normalization.BatchNormalization object at 0x7ff2862e
6590>
5 <keras.layers.pooling.max_pooling2d.MaxPooling2D object at 0x7ff25fdaba90>
6 <keras.layers.convolutional.conv2d.Conv2D object at 0x7ff194bbf710>
7 <keras.layers.normalization.batch_normalization.BatchNormalization object at 0x7ff25fda
5b50>
8 <keras.layers.pooling.max_pooling2d.MaxPooling2D object at 0x7ff194d988d0>
9 <keras.layers.reshaping.flatten.Flatten object at 0x7ff25ffcd7d0>
10 <keras.layers.core.dense.Dense object at 0x7ff25fdbfc10>
11 <keras.layers.normalization.batch_normalization.BatchNormalization object at 0x7ff2668
dd710>
12 <keras.layers.core.dense.Dense object at 0x7ff25fd60350>
13 <keras.layers.core.activation.Activation object at 0x7ff2668db3d0>
14 <keras.layers.normalization.batch_normalization.BatchNormalization object at 0x7ff25fd
abf50>
15 <keras.layers.core.dense.Dense object at 0x7ff25fd46390>
16 <keras.layers.core.activation.Activation object at 0x7ff25fd46590>
17 <keras.layers.normalization.batch_normalization.BatchNormalization object at 0x7ff2f44
bf8d0>
18 <keras.layers.core.dense.Dense object at 0x7ff25fd5a450>
19 <keras.layers.core.activation.Activation object at 0x7ff25fd4e250>
```

In [72]:

```
model_CNN.layers[-2]
```

Out[72]:

```
<keras.layers.core.dense.Dense at 0x7ff25fd5a450>
```

In [73]:

```
import os
os.environ["KERAS_BACKEND"] = "tensorflow"
kerasBKED = os.environ["KERAS_BACKEND"]
print(kerasBKED)
```

```
tensorflow
```

Separating Features Layers from the CNN Model

In [74]:

```
import tensorflow as tf
# feature_extractor = tf.keras.Model(inputs=model_CNN.input,
#                                    outputs=model_CNN.get_layer(-2).output)
# output_layers_model =tf.keras.Model(inputs=model_CNN.input, outputs=model_CNN.output)
# cnn_layer_output = model_CNN.layers[-2].output
# cnn_model_features = tf.keras.Model(inputs=model_CNN.input, outputs=cnn_layer_output)
cnn_model_features = tf.keras.Model(inputs=model_CNN.input, outputs=model_CNN.layers[-3]
.output)
```

Extracting Features from CNN Model

In [75]:

```
# Extract features from input data using the CNN model
X_train_cnn = cnn_model_features.predict(X_train)
X_test_cnn = cnn_model_features.predict(X_test)
```

```
1174/1174 [==============================] - 3s 2ms/step
294/294 [==============================] - 1s 2ms/step
```

Integrating CNN with SVM Classifier using Grid Search for Best Perameters

In [76]:

```
import numpy as np
from sklearn.svm import SVC
from sklearn.model_selection import GridSearchCV

clf=SVC(kernel='rbf',C=100,gamma=0.001)
kf=KFold(n_splits=5)
scores_SVM = cross_val_score(clf, X_train_cnn, Y_train, cv=kf)
print(scores_SVM)
print("%0.2f accuracy with a standard deviation of %0.2f" % (scores_SVM.mean(), scores_SV
M.std()))
clf.fit(X_train_cnn, Y_train)
# Evaluate the combined CNN-SVM model on a test dataset
svm_accuracy = clf.score(X_test_cnn, Y_test)
print('SVM Accuracy:', svm_accuracy*100)
y_testSVM = clf.predict(X_test_cnn)
```

```
[0.99960053 1.         1.         0.99986683 0.98242109]
1.00 accuracy with a standard deviation of 0.01
SVM Accuracy: 98.72163630552893
```

In [77]:

```
svm_accuracy = clf.score(X_test_cnn, Y_test)
print('SVM Accuracy:', svm_accuracy*100)
```

```
SVM Accuracy: 98.72163630552893
```

In [78]:

```
from sklearn.metrics import confusion_matrix, classification_report, accuracy_score

print(classification_report(Y_test, y_testSVM,target_names=target_names))
print("Accuracy: {0}".format(accuracy_score(Y_test, y_testSVM)*100))
```

```
              precision    recall  f1-score   support

       akiec       1.00      1.00      1.00      1359
         bcc       1.00      1.00      1.00      1318
         bkl       0.97      0.99      0.98      1262
          df       1.00      1.00      1.00      1351
          nv       0.98      0.93      0.96      1374
        vasc       1.00      1.00      1.00      1358
         mel       0.97      0.99      0.98      1365

    accuracy                           0.99      9387
   macro avg       0.99      0.99      0.99      9387
weighted avg       0.99      0.99      0.99      9387

Accuracy: 98.72163630552893
```

Integrating CNN with Random Forest Classifier using Grid Search for Best Perameters

In [79]:

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
rgclf = RandomForestClassifier(max_depth=3,
               max_features=1,
               min_samples_split=3,
               bootstrap=False,
               criterion=  "entropy",
               n_estimators=20)
kf=KFold(n_splits=5)
scores_RF = cross_val_score(rgclf, X_train_cnn, Y_train, cv=kf)
print(scores_RF)
print("%0.2f accuracy with a standard deviation of %0.2f" % (scores_RF.mean(), scores_RF.
std()))
rgclf.fit(X_train_cnn, Y_train)
RFC_accuracy = rgclf.score(X_test_cnn, Y_test)
print('Random Forest Classifier Accuracy:', RFC_accuracy*100)
y_test_RF = rgclf.predict(X_test_cnn)
print("Accuracy: {0}".format(accuracy_score(Y_test, y_test_RF)*100))
```

```
[0.99494008 0.99121172 0.99747004 0.99467306 0.96723931]
0.99 accuracy with a standard deviation of 0.01
Random Forest Classifier Accuracy: 97.31543624161074
Accuracy: 97.31543624161074
```

In [80]:

```
y_test_RF = rgclf.predict(X_test_cnn)
print("Accuracy: {0}".format(accuracy_score(Y_test, y_test_RF)*100))
```

```
Accuracy: 97.31543624161074
```

In [81]:

```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import GridSearchCV

# parameters = {"n_neighbors": [1],
#               "weights": ['uniform', 'distance'],
#               "metric": ['minkowski','euclidean','manhattan'],
```

```
#                "algorithm": ['auto', 'ball_tree', 'kd_tree', 'brute']}
kgclf = KNeighborsClassifier(n_neighbors=1,
              weights='distance',
              metric='euclidean',
              algorithm= 'auto')
kf=KFold(n_splits=5)
scores_KNN = cross_val_score(kgclf, X_train_cnn, Y_train, cv=kf)
print("%0.2f accuracy with a standard deviation of %0.2f" % (scores_KNN.mean(), scores_KN
N.std()))
kgclf.fit(X_train_cnn, Y_train)
KNN_accuracy = kgclf.score(X_test_cnn, Y_test)
print('KNN Classifier Accuracy:', KNN_accuracy*100)
```

```
1.00 accuracy with a standard deviation of 0.01
KNN Classifier Accuracy: 98.9879620752104
```

In [82]:

```
y_testKNN = kgclf.predict(X_test_cnn)
from sklearn.metrics import confusion_matrix, classification_report, accuracy_score

print(classification_report(Y_test, y_testKNN,target_names=target_names))
print("Accuracy Score: {0}".format(accuracy_score(Y_test, y_testKNN)*100))
```

```
              precision    recall  f1-score   support

       akiec       1.00      1.00      1.00      1359
         bcc       0.99      1.00      1.00      1318
         bkl       0.97      1.00      0.99      1262
          df       1.00      1.00      1.00      1351
          nv       1.00      0.93      0.96      1374
        vasc       1.00      1.00      1.00      1358
         mel       0.97      1.00      0.98      1365

    accuracy                           0.99      9387
   macro avg       0.99      0.99      0.99      9387
weighted avg       0.99      0.99      0.99      9387

Accuracy Score: 98.9879620752104
```

Integrating CNN with Logistic Regression Classifier using Grid Search for Best Perameters

In [83]:

```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix, classification_report, accuracy_score



# Create a logistic regression object
grid_search_LR = LogisticRegression(C=100,
              penalty='l2')
kf=KFold(n_splits=5)
scores_LR = cross_val_score(grid_search_LR, X_train_cnn, Y_train, cv=kf)
print(scores_LR)
print("%0.2f accuracy with a standard deviation of %0.2f" % (scores_LR.mean(), scores_LR.
std()))
# Perform grid search with 5-fold cross-validation
grid_search_LR.fit(X_train_cnn, Y_train)

# Print the best hyperparameters and the corresponding accuracy score
y_test_LR = grid_search_LR.predict(X_test_cnn)

print(classification_report(Y_test, y_test_LR,target_names=target_names))
print("Accuracy: {0}".format(accuracy_score(Y_test, y_test_LR)*100))
```

```
/opt/conda/lib/python3.7/site-packages/sklearn/linear_model/_logistic.py:818: Convergence
```

```
Warning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG,
/opt/conda/lib/python3.7/site-packages/sklearn/linear_model/_logistic.py:818: Convergence
Warning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG,
/opt/conda/lib/python3.7/site-packages/sklearn/linear_model/_logistic.py:818: Convergence
Warning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG,
/opt/conda/lib/python3.7/site-packages/sklearn/linear_model/_logistic.py:818: Convergence
Warning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG,
/opt/conda/lib/python3.7/site-packages/sklearn/linear_model/_logistic.py:818: Convergence
Warning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG,
```

```
[0.99946738 1.         1.         0.99986683 0.98295379]
1.00 accuracy with a standard deviation of 0.01
              precision    recall  f1-score   support

       akiec       1.00      1.00      1.00      1359
         bcc       1.00      1.00      1.00      1318
         bkl       0.97      0.99      0.98      1262
          df       1.00      1.00      1.00      1351
          nv       0.98      0.93      0.95      1374
        vasc       1.00      1.00      1.00      1358
         mel       0.97      0.99      0.98      1365

    accuracy                           0.99      9387
   macro avg       0.99      0.99      0.99      9387
weighted avg       0.99      0.99      0.99      9387

Accuracy: 98.68967721316714
```

```
/opt/conda/lib/python3.7/site-packages/sklearn/linear_model/_logistic.py:818: Convergence
Warning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG,
```

In [ ]:

```

```

In [ ]:

```

```

In [ ]:

```

```