In [ ]:

```

```

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 [1]:

```
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
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 [2]:

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

Out[2]:

	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 Cleaning

In [3]:

```
data['label'].unique()
```

Out[3]:

```
array([2, 4, 3, 6, 5, 1, 0])
```

In [4]:

```
y = data['label']
x = data.drop(columns = ['label'])
```

In [5]:

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

Out[5]:

```
0
```

In [6]:

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

Out[6]:

	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 [7]:

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

Out[7]:

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

In [8]:

```
y = data['label']
x = data.drop(columns = ['label'])
```

In [9]:

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

Out[9]:

```
0
```

In [10]:

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

Out[10]:

	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 [11]:

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

Out[11]:

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

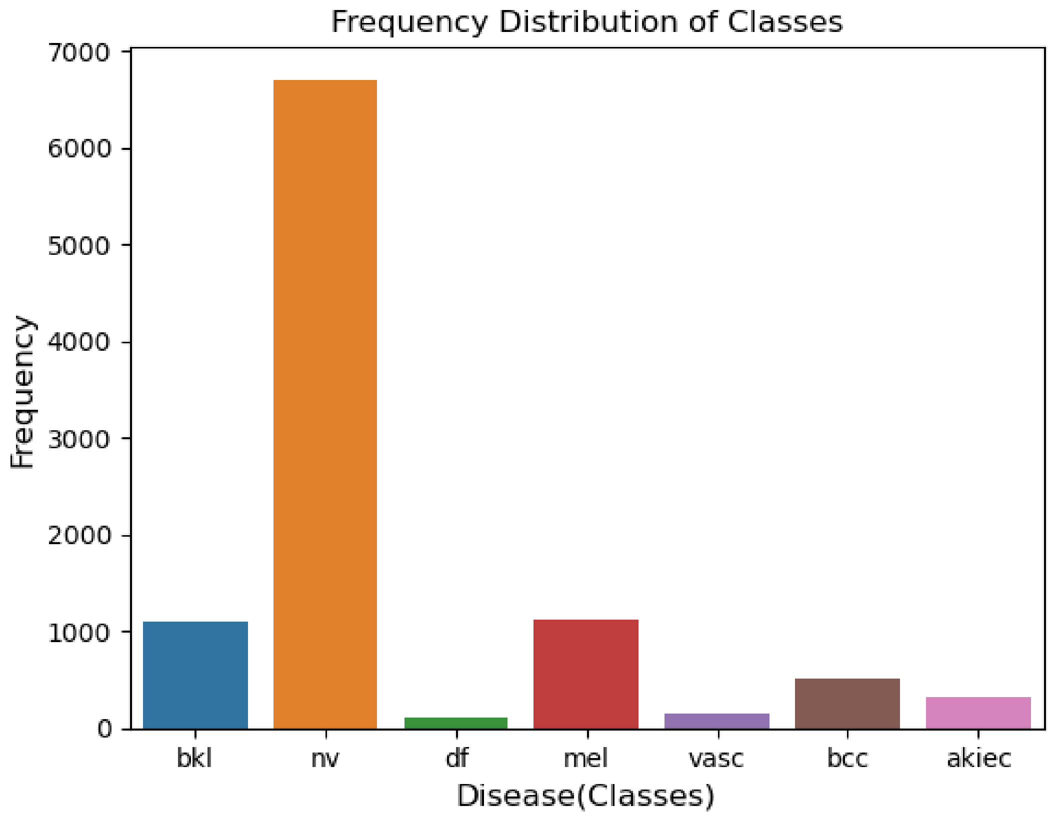
Exploratory Data Analysis

In [12]:

```
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[12]:

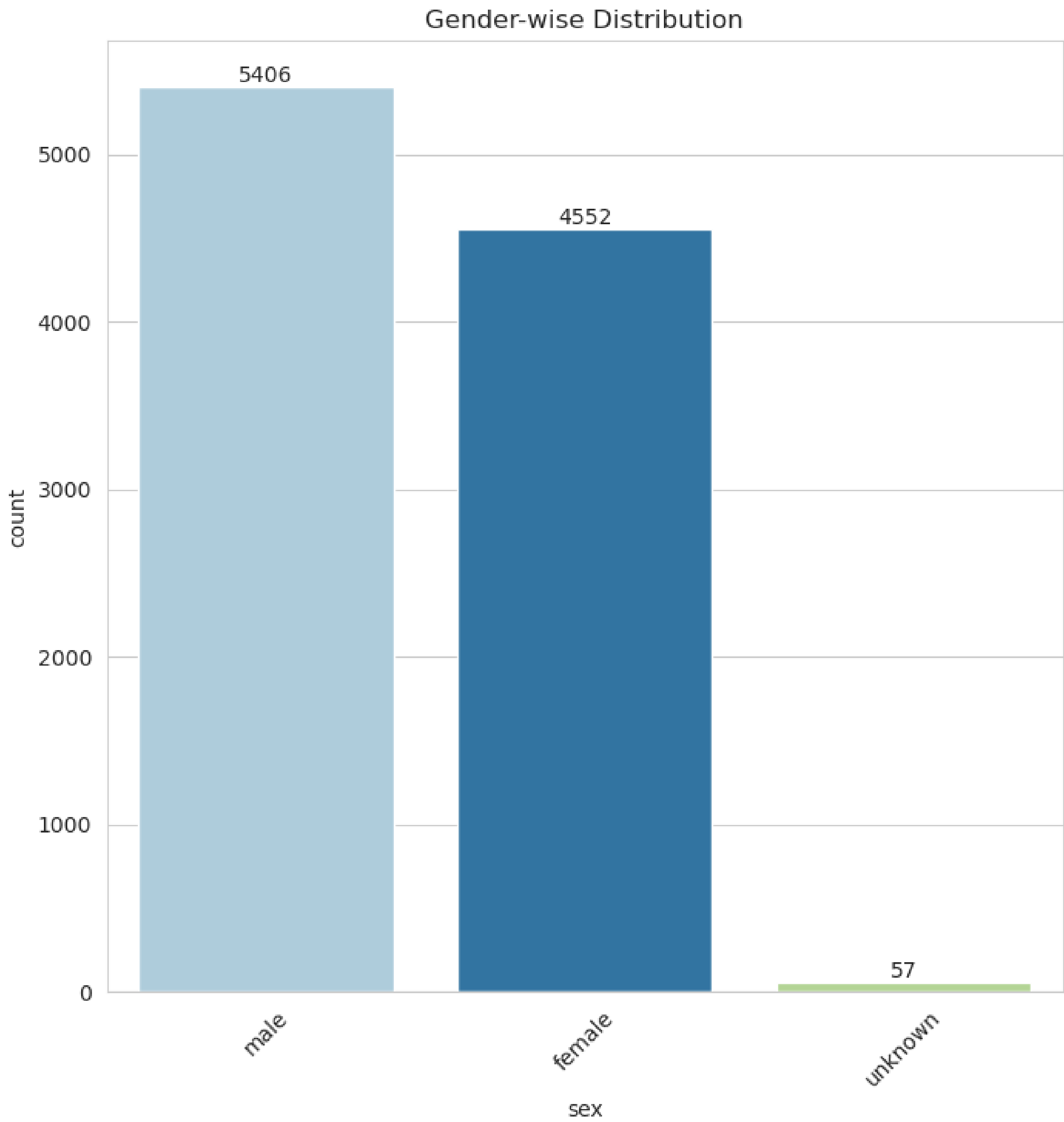
```
Text(0.5, 1.0, 'Frequency Distribution of Classes')
```



In [13]:

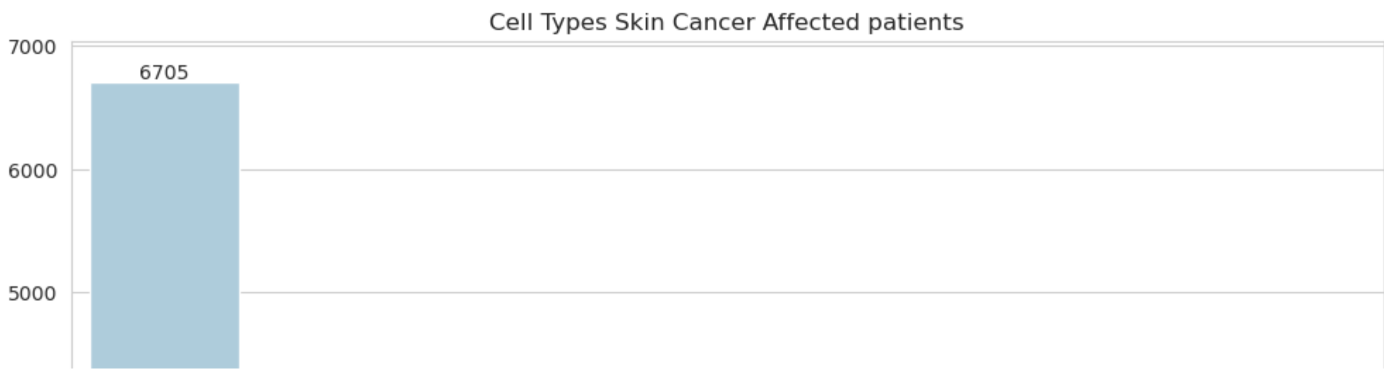
```
sns.set_style('whitegrid')
colors = ['#87ace8','#e3784d', 'green']
fig,axes = plt.subplots(figsize=(8,8))

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

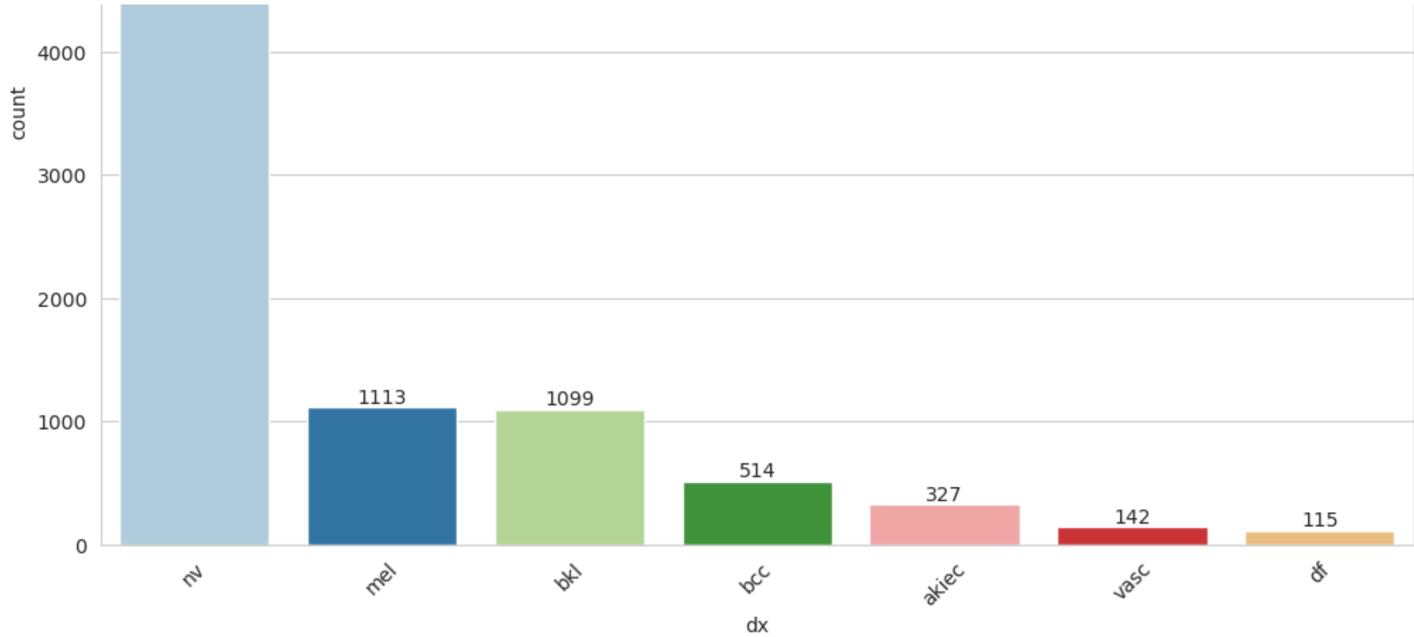
```
plt.xticks(rotation=45)
plt.show()
```



In [14]:

```
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 [ ]:

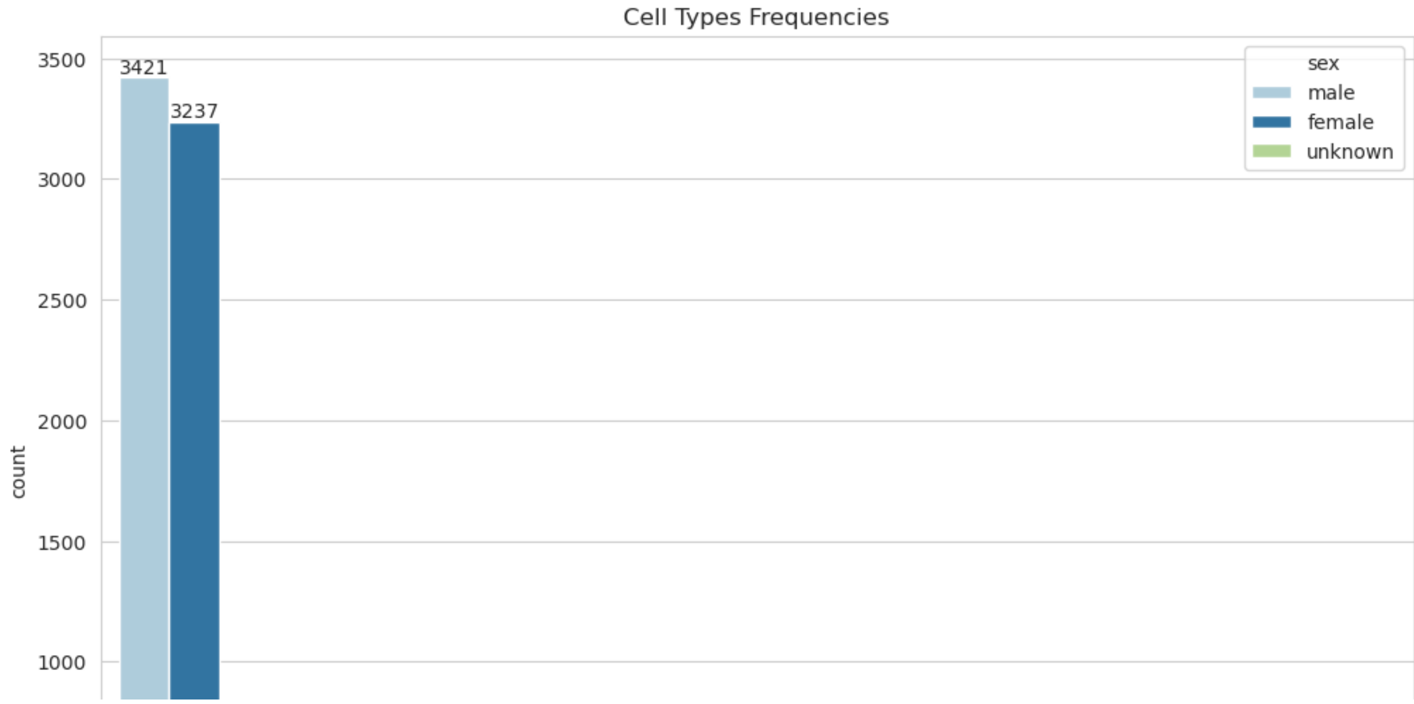
In [15]:

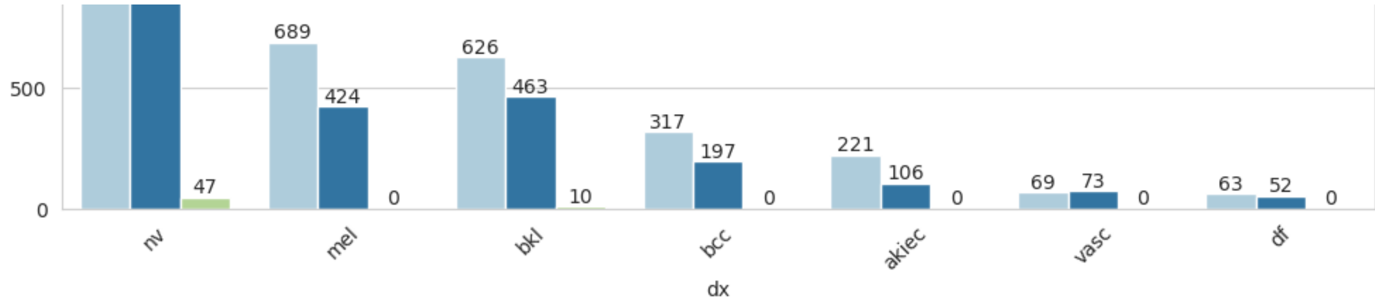
```
classes = {2:'bkl', 4:'nv', 3:'df', 6:'mel', 5:'vasc', 1:'bcc', 0:'akiec'}

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

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

In [16]:

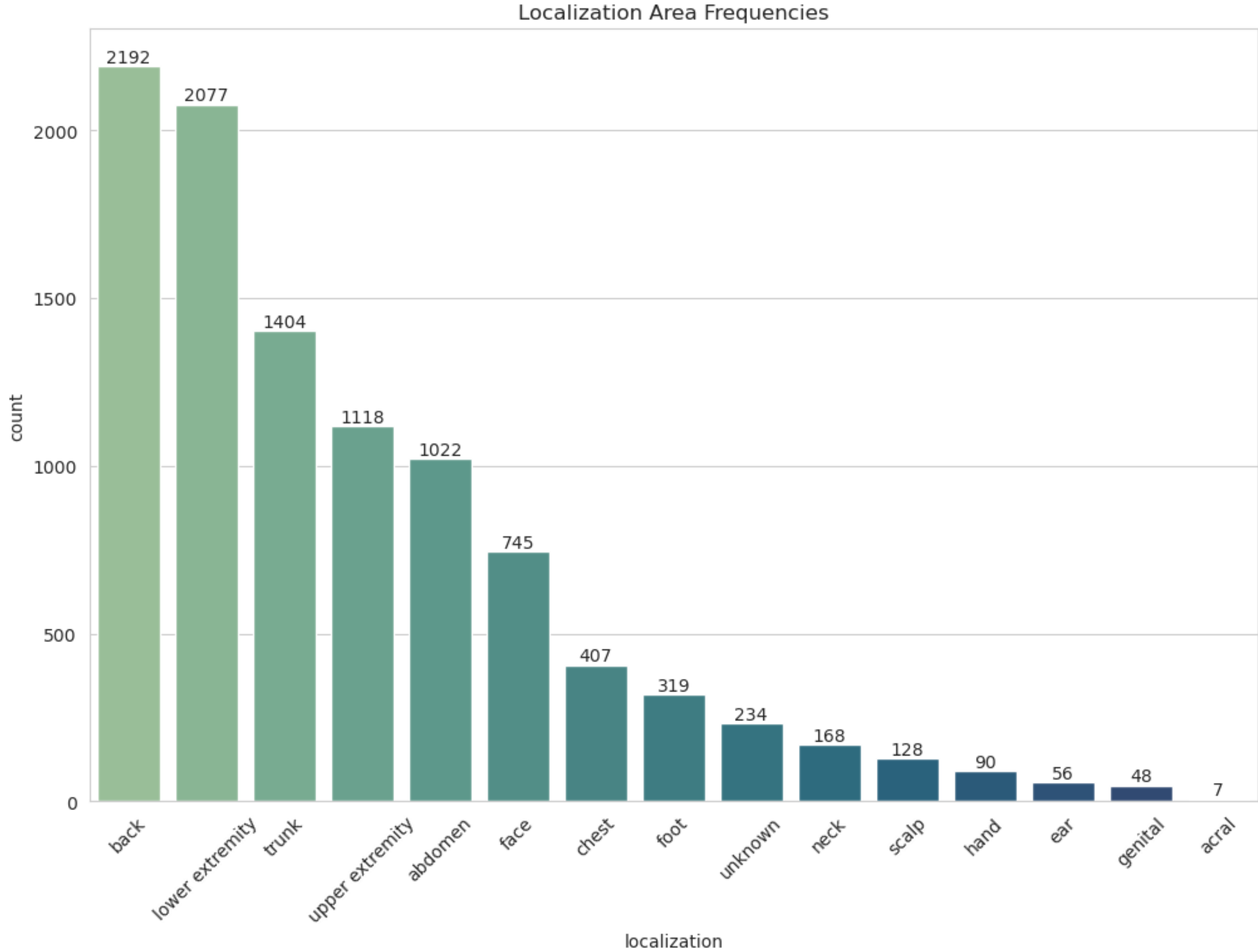
```
sns.set_style('whitegrid')
fig,axes = plt.subplots(figsize=(12,8))
ax = sns.countplot(x='dx',hue='sex', data=meta_data, order = meta_data['dx'].value_count
s().index, palette = 'Paired')
for container in ax.containers:
    ax.bar_label(container)
plt.title('Cell Types Frequencies')
plt.xticks(rotation=45)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





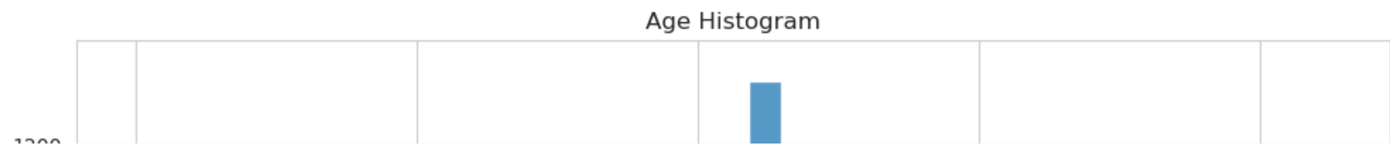
In [17]:

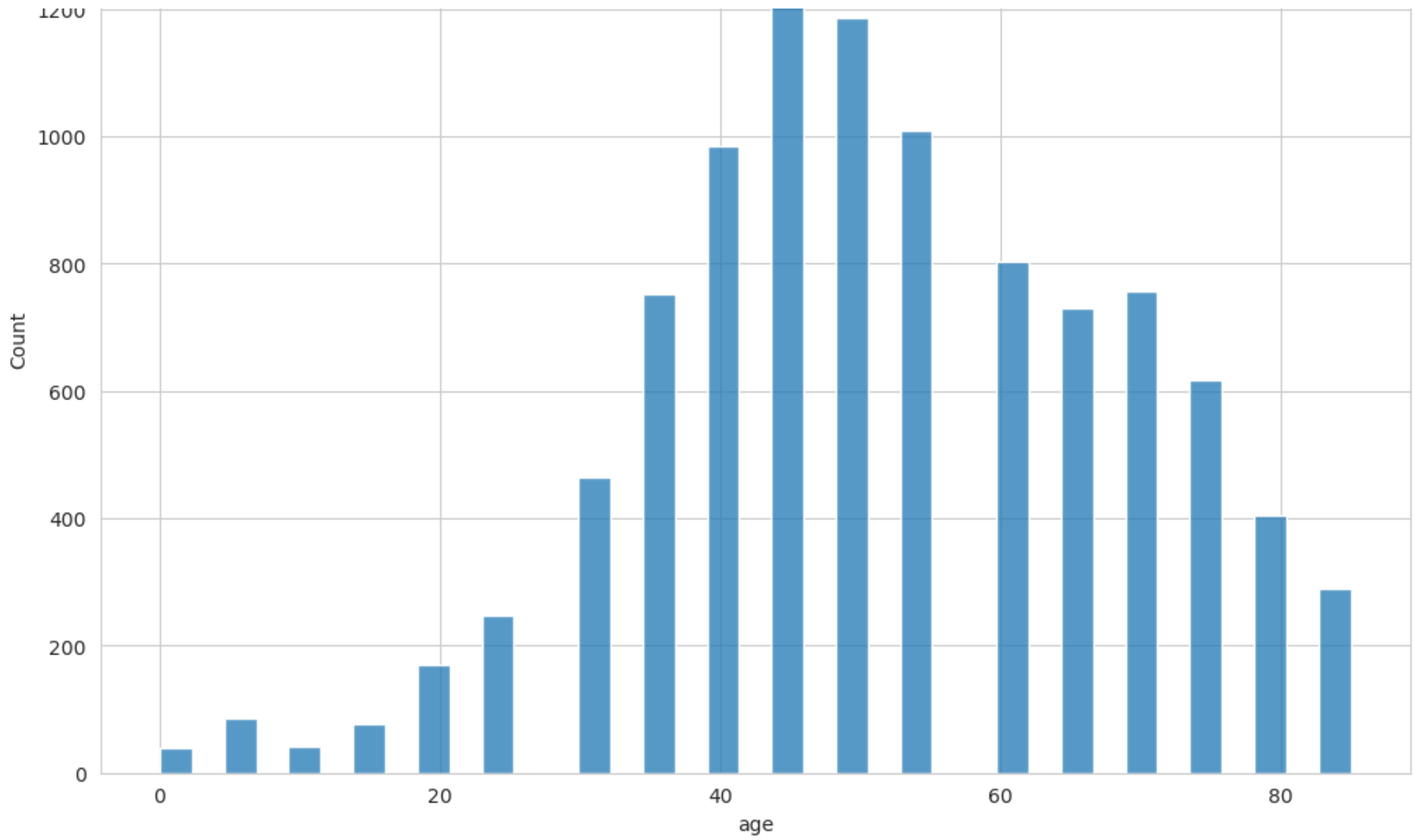
```
sns.set_style('whitegrid')
fig,axes = plt.subplots(figsize=(12,8))
ax = sns.countplot(x='localization',data=meta_data, order = meta_data['localization'].val
ue_counts().index, palette = 'crest')
for container in ax.containers:
    ax.bar_label(container)
plt.title('Localization Area Frequencies')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



In [18]:

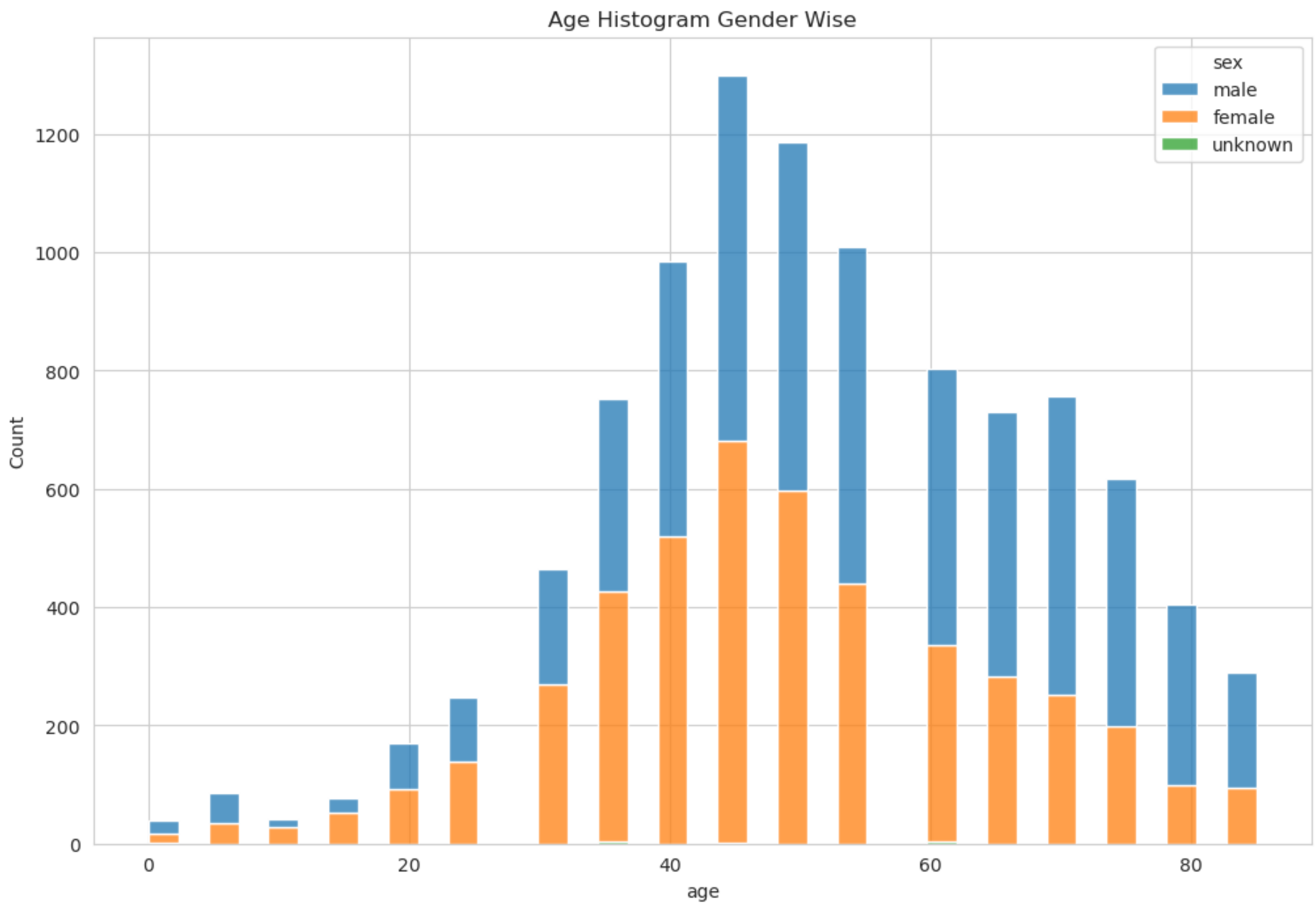
```
sns.set_style('whitegrid')
fig,axes = plt.subplots(figsize=(12,8))
ax = sns.histplot(data=meta_data, x='age')
plt.title('Age Histogram')
plt.show()
```





In [19]:

```
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()
```



In [20]:

```
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 [21]:

```
# 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 [22]:

```
# 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 [23]:

```
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"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 conv2d (Conv2D)             (None, 28, 28, 32)        896       
                                                                 
 batch_normalization (BatchN  (None, 28, 28, 32)       128       
 ormalization)                                                   
                                                                 
 max_pooling2d (MaxPooling2D  (None, 14, 14, 32)       0         
 )                                                               
                                                                 
 conv2d_1 (Conv2D)           (None, 14, 14, 64)        18496     
                                                                 
 batch_normalization_1 (Batc  (None, 14, 14, 64)       256       
 hNormalization)                                                 
                                                                 
 max_pooling2d_1 (MaxPooling  (None, 7, 7, 64)         0         
 2D)                                                             
                                                                 
 conv2d_2 (Conv2D)           (None, 7, 7, 128)         73856     
                                                                 
 batch_normalization_2 (Batc  (None, 7, 7, 128)        512       
 hNormalization)                                                 
                                                                 
 max_pooling2d_2 (MaxPooling  (None, 4, 4, 128)        0         
 2D)                                                             
                                                                 
 flatten (Flatten)           (None, 2048)              0         
                                                                 
 dense (Dense)               (None, 64)                131136    
                                                                 
 batch_normalization_3 (Batc  (None, 64)               256       
 hNormalization)                                                 
                                                                 
 dense_1 (Dense)             (None, 32)                2080      
                                                                 
 activation (Activation)     (None, 32)                0         
                                                                 
 batch_normalization_4 (Batc  (None, 32)               128       
 hNormalization)                                                 
                                                                 
 dense_2 (Dense)             (None, 16)                528       
                                                                 
 activation_1 (Activation)   (None, 16)                0         
                                                                 
 batch_normalization_5 (Batc  (None, 16)               64        
 hNormalization)                                                 
                                                                 
 dense_3 (Dense)             (None, 7)                 119       
                                                                 
 activation_2 (Activation)   (None, 7)                 0         
                                                                 
=================================================================
Total params: 228,455
Trainable params: 227,783
Non-trainable params: 672
_________________________________________________________________
None
```

In [24]:

```
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 [==============================] - 15s 10ms/step - loss: 0.9542 - accuracy: 0.663
5 - val_loss: 0.9318 - val_accuracy: 0.6377 - lr: 0.0010
Epoch 2/50
470/470 [==============================] - 4s 8ms/step - loss: 0.4104 - accuracy: 0.8578
- val_loss: 0.8866 - val_accuracy: 0.6979 - lr: 0.0010
Epoch 3/50
470/470 [==============================] - 4s 8ms/step - loss: 0.2900 - accuracy: 0.9001
- val_loss: 0.6961 - val_accuracy: 0.7650 - lr: 0.0010
Epoch 4/50
470/470 [==============================] - 4s 8ms/step - loss: 0.1956 - accuracy: 0.9325
- val_loss: 0.4986 - val_accuracy: 0.8198 - lr: 0.0010
Epoch 5/50
470/470 [==============================] - 4s 8ms/step - loss: 0.1521 - accuracy: 0.9478
- val_loss: 0.4333 - val_accuracy: 0.8583 - lr: 0.0010
Epoch 6/50
470/470 [==============================] - 4s 8ms/step - loss: 0.1286 - accuracy: 0.9552
- val_loss: 0.4032 - val_accuracy: 0.8720 - lr: 0.0010
Epoch 7/50
470/470 [==============================] - 4s 8ms/step - loss: 0.0947 - accuracy: 0.9682
- val_loss: 0.1674 - val_accuracy: 0.9463 - lr: 0.0010
Epoch 8/50
470/470 [==============================] - 4s 8ms/step - loss: 0.0844 - accuracy: 0.9713
- val_loss: 1.3121 - val_accuracy: 0.6088 - lr: 0.0010
Epoch 9/50
470/470 [==============================] - 4s 8ms/step - loss: 0.1012 - accuracy: 0.9646
- val_loss: 0.8057 - val_accuracy: 0.7658 - lr: 0.0010
Epoch 10/50
467/470 [============================>.] - ETA: 0s - loss: 0.0704 - accuracy: 0.9767
Epoch 10: ReduceLROnPlateau reducing learning rate to 0.00010000000474974513.
470/470 [==============================] - 4s 9ms/step - loss: 0.0705 - accuracy: 0.9767
- val_loss: 0.2393 - val_accuracy: 0.9178 - lr: 0.0010
Epoch 11/50
470/470 [==============================] - 4s 9ms/step - loss: 0.0214 - accuracy: 0.9943
- val_loss: 0.0746 - val_accuracy: 0.9794 - lr: 1.0000e-04
Epoch 12/50
470/470 [==============================] - 4s 8ms/step - loss: 0.0119 - accuracy: 0.9976
- val_loss: 0.0778 - val_accuracy: 0.9798 - lr: 1.0000e-04
Epoch 13/50
470/470 [==============================] - 4s 8ms/step - loss: 0.0093 - accuracy: 0.9982
- val_loss: 0.0703 - val_accuracy: 0.9811 - lr: 1.0000e-04
Epoch 14/50
470/470 [==============================] - 4s 8ms/step - loss: 0.0064 - accuracy: 0.9993
- val_loss: 0.0760 - val_accuracy: 0.9796 - lr: 1.0000e-04
Epoch 15/50
470/470 [==============================] - 4s 8ms/step - loss: 0.0048 - accuracy: 0.9996
- val_loss: 0.0708 - val_accuracy: 0.9822 - lr: 1.0000e-04
Epoch 16/50
469/470 [============================>.] - ETA: 0s - loss: 0.0049 - accuracy: 0.9993
Epoch 16: ReduceLROnPlateau reducing learning rate to 1.0000000474974514e-05.
470/470 [==============================] - 4s 8ms/step - loss: 0.0049 - accuracy: 0.9993
- val_loss: 0.0831 - val_accuracy: 0.9794 - lr: 1.0000e-04
Epoch 17/50
470/470 [==============================] - 4s 9ms/step - loss: 0.0039 - accuracy: 0.9996
- val_loss: 0.0709 - val_accuracy: 0.9816 - lr: 1.0000e-05
Epoch 18/50
470/470 [==============================] - 4s 9ms/step - loss: 0.0034 - accuracy: 0.9997
- val_loss: 0.0718 - val_accuracy: 0.9818 - lr: 1.0000e-05
Epoch 19/50
470/470 [==============================] - ETA: 0s - loss: 0.0035 - accuracy: 0.9997
Epoch 19: ReduceLROnPlateau reducing learning rate to 1.0000000656873453e-06.
470/470 [==============================] - 4s 9ms/step - loss: 0.0035 - accuracy: 0.9997
- val_loss: 0.0708 - val_accuracy: 0.9820 - lr: 1.0000e-05
Epoch 20/50
470/470 [==============================] - 4s 8ms/step - loss: 0.0030 - accuracy: 0.9998
- val_loss: 0.0717 - val_accuracy: 0.9816 - lr: 1.0000e-06
Epoch 21/50
```

```
470/470 [==============================] - 4s 8ms/step - loss: 0.0031 - accuracy: 0.9998
- val_loss: 0.0714 - val_accuracy: 0.9812 - lr: 1.0000e-06
Epoch 22/50
469/470 [============================>.] - ETA: 0s - loss: 0.0028 - accuracy: 0.9999
Epoch 22: ReduceLROnPlateau reducing learning rate to 1.0000001111620805e-07.
470/470 [==============================] - 4s 8ms/step - loss: 0.0028 - accuracy: 0.9999
- val_loss: 0.0708 - val_accuracy: 0.9819 - lr: 1.0000e-06
Epoch 23/50
470/470 [==============================] - 4s 8ms/step - loss: 0.0030 - accuracy: 0.9998
- val_loss: 0.0715 - val_accuracy: 0.9818 - lr: 1.0000e-07
Epoch 23: early stopping
```

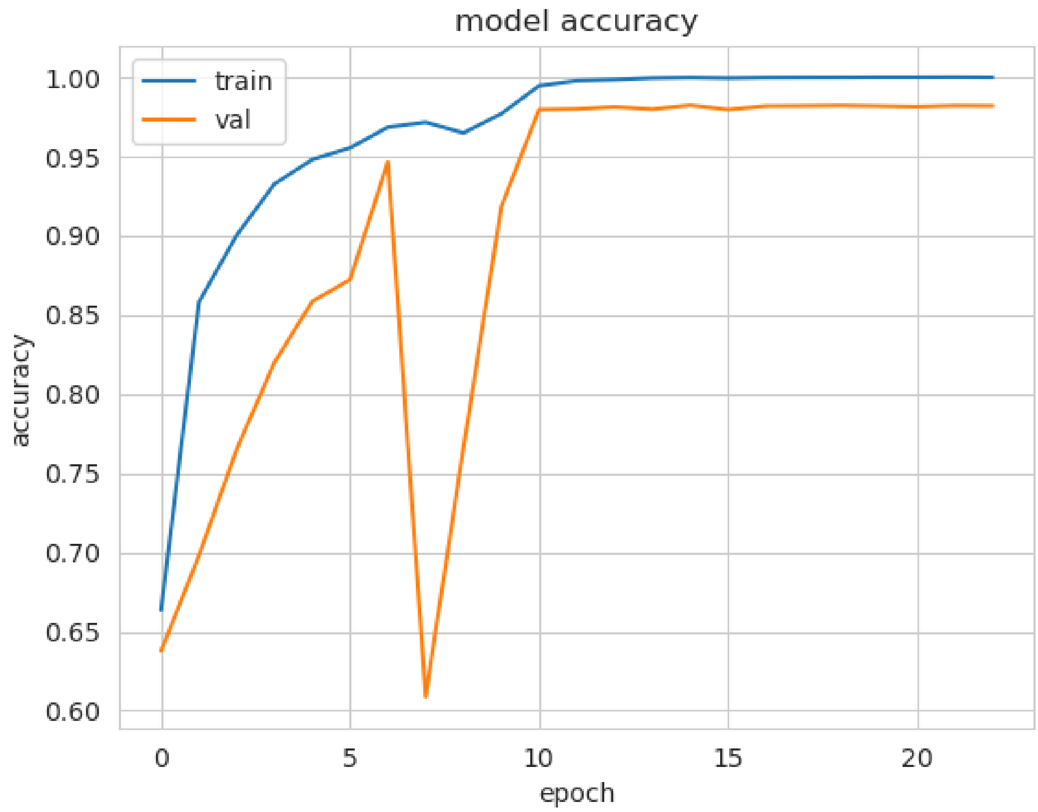
In [25]:

```
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: 0.07844
    Test Accuracy: 97.93%
```

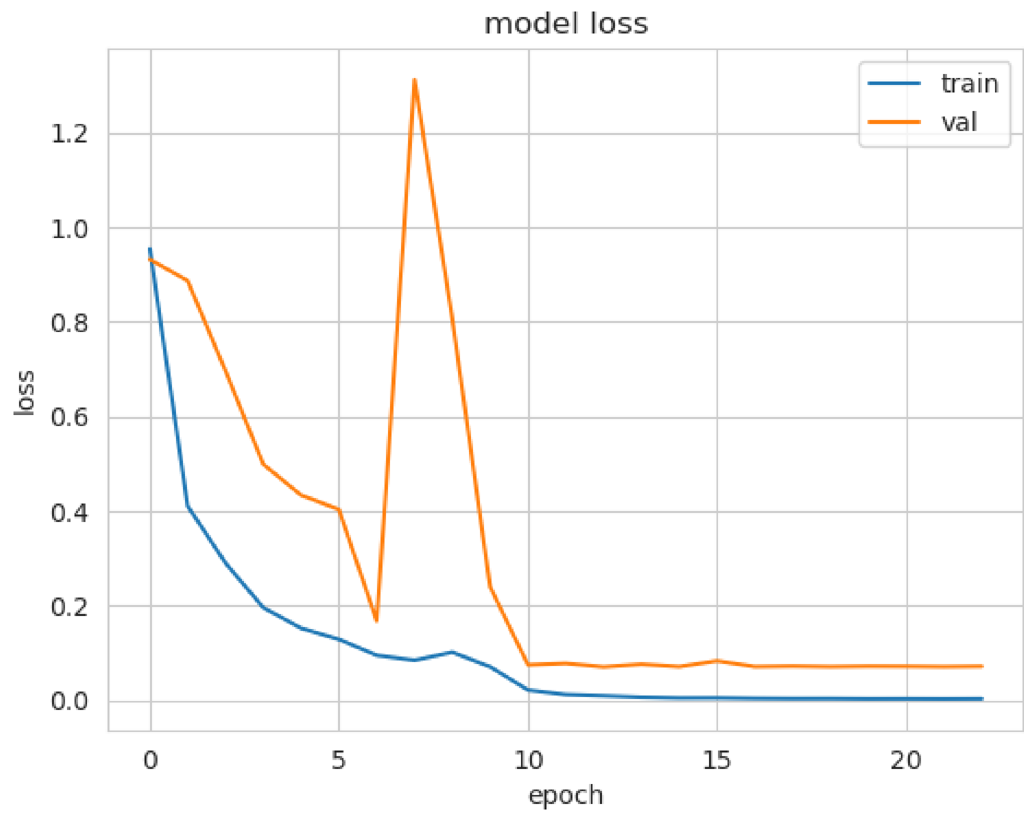
In [26]:

```
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 [27]:

```
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 [28]:

```
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]
```

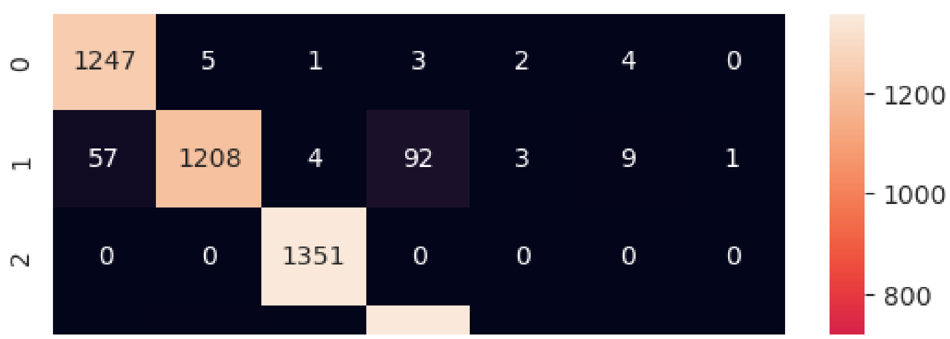
In [29]:

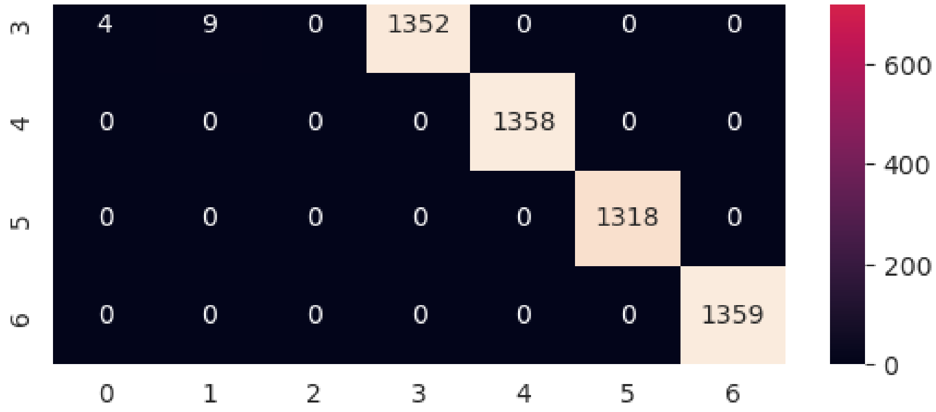
```
cm_CNN = confusion_matrix(y_true_CNN,y_pred_CNN,labels=classes_labels)
print(confusion_matrix(y_true_CNN,y_pred_CNN,labels=classes_labels))
sns.heatmap(cm_CNN, annot = True, fmt='')
```

```
[[1247    5    1    3    2    4    0]
 [  57 1208    4   92    3    9    1]
 [   0    0 1351    0    0    0    0]
 [   4    9    0 1352    0    0    0]
 [   0    0    0    0 1358    0    0]
 [   0    0    0    0    0 1318    0]
 [   0    0    0    0    0    0 1359]]
```

Out[29]:

```
<AxesSubplot:>
```





In [30]:

```
#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 [31]:

```
#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 3ms/step
CNN Model Prediction Results
              precision    recall  f1-score   support

       akiec       1.00      1.00      1.00      1359
         bcc       0.99      1.00      1.00      1318
         bkl       0.95      0.99      0.97      1262
          df       1.00      1.00      1.00      1351
          nv       0.99      0.88      0.93      1374
        vasc       1.00      1.00      1.00      1358
         mel       0.93      0.99      0.96      1365

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

In [32]:

```
# 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 0x7fc69fc93390>
1 <keras.layers.normalization.batch_normalization.BatchNormalization object at 0x7fc69fd3
d310>
2 <keras.layers.pooling.max_pooling2d.MaxPooling2D object at 0x7fc6a00f7b50>
3 <keras.layers.convolutional.conv2d.Conv2D object at 0x7fc70e4c4e90>
4 <keras.layers.normalization.batch_normalization.BatchNormalization object at 0x7fc6a011
3110>
5 <keras.layers.pooling.max_pooling2d.MaxPooling2D object at 0x7fc6a00f7950>
6 <keras.layers.convolutional.conv2d.Conv2D object at 0x7fc6a010db10>
7 <keras.layers.normalization.batch_normalization.BatchNormalization object at 0x7fc6a010
5110>
8 <keras.layers.pooling.max_pooling2d.MaxPooling2D object at 0x7fc69ff02390>
9 <keras.layers.reshaping.flatten.Flatten object at 0x7fc69fef5250>
10 <keras.layers.core.dense.Dense object at 0x7fc6a0105e90>
11 <keras.layers.normalization.batch_normalization.BatchNormalization object at 0x7fc6a01
05690>
12 <keras.layers.core.dense.Dense object at 0x7fc69ff16650>
13 <keras.layers.core.activation.Activation object at 0x7fc6a04ad450>
14 <keras.layers.normalization.batch_normalization.BatchNormalization object at 0x7fc69fe
ec0d0>
15 <keras.layers.core.dense.Dense object at 0x7fc69ff0a0d0>
16 <keras.layers.core.activation.Activation object at 0x7fc69fef5f10>
17 <keras.layers.normalization.batch_normalization.BatchNormalization object at 0x7fc69ff
16390>
18 <keras.layers.core.dense.Dense object at 0x7fc69ff0fe10>
19 <keras.layers.core.activation.Activation object at 0x7fc69ff02e50>
```

In [33]:

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

Out[33]:

```
<keras.layers.core.dense.Dense at 0x7fc69ff0fe10>
```

In [34]:

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

```
tensorflow
```

Separating Features Layers from the CNN Model

In [35]:

```
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 [36]:

```
# 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 [37]:

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

parameters = {'kernel':['rbf'],
              'C':[1, 10, 100, 1000],
              'gamma':[1e-3, 1e-4]}
clf = GridSearchCV(SVC(), parameters)
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)
```

```
SVM Accuracy: 98.60445296686908
```

In [38]:

```
svm_accuracy = clf.score(X_test_cnn, Y_test)
print('SVM Accuracy:', svm_accuracy*100)
svmclf = clf.best_estimator_
print(svmclf)
svmclf.fit(X_train_cnn, Y_train)
print("Accuracy: {0}".format(accuracy_score(Y_test, y_testSVM)*100))
```

```
SVM Accuracy: 98.60445296686908
SVC(C=10, gamma=0.001)
Accuracy: 98.60445296686908
```

In [39]:

```
y_testSVM = svmclf.predict(X_test_cnn)
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       0.99      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       0.96      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: 98.60445296686908
```

In [ ]:

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

In [40]:

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV

parameters = {"max_depth": [3, None],
              "max_features": [1, 3, 10],
              "min_samples_split": [1.0, 3, 10],
              "min_samples_leaf": [1, 3, 10],
              "bootstrap": [True, False],
              "criterion": ["gini", "entropy"],
              "n_estimators": [10, 20, 50]}
rclf = RandomForestClassifier()
rgclf = GridSearchCV(rclf, param_grid=parameters)
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))
```

```
Random Forest Classifier Accuracy: 99.03057419835943
Accuracy: 99.03057419835943
```

In [41]:

```
y_test_RF = rgclf.predict(X_test_cnn)
print("Accuracy: {0}".format(accuracy_score(Y_test, y_test_RF)*100))
RFclf = rgclf.best_estimator_
print(RFclf)
y_testRFC = RFclf.predict(X_test_cnn)
from sklearn.metrics import confusion_matrix, classification_report, accuracy_score

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

```
Accuracy: 99.03057419835943
RandomForestClassifier(max_features=10, min_samples_split=3, n_estimators=20)
              precision    recall  f1-score   support

       akiec       1.00      1.00      1.00      1359
         bcc       1.00      1.00      1.00      1318
         bkl       0.97      1.00      0.99      1262
          df       1.00      1.00      1.00      1351
          nv       1.00      0.94      0.97      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: 99.03057419835943
```

Integrating CNN with KNN Classifier using Grid Search for Best Perameters

In [42]:

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

parameters = {"n_neighbors": [1, 5, 10,30],
              "weights": ['uniform', 'distance'],
              "metric": ['minkowski','euclidean','manhattan'],
```

```
                  "algorithm": ['auto', 'ball_tree', 'kd_tree', 'brute']}
kclf = KNeighborsClassifier()
kgclf = GridSearchCV(kclf, param_grid=parameters)
kgclf.fit(X_train_cnn, Y_train)
KNN_accuracy = kgclf.score(X_test_cnn, Y_test)
print('KNN Classifier Accuracy:', KNN_accuracy*100)
```

```
KNN Classifier Accuracy: 98.68967721316714
```

In [43]:

```
y_testKNN = kgclf.predict(X_test_cnn)
KNNclf = kgclf.best_estimator_
print(KNNclf)
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))
```

```
KNeighborsClassifier(n_neighbors=10, weights='distance')
              precision    recall  f1-score   support

       akiec       1.00      1.00      1.00      1359
         bcc       0.99      1.00      1.00      1318
         bkl       0.96      1.00      0.98      1262
          df       1.00      1.00      1.00      1351
          nv       1.00      0.92      0.96      1374
        vasc       1.00      1.00      1.00      1358
         mel       0.96      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: 98.68967721316714
```

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

In [44]:

```
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
lr = LogisticRegression()

# Define the hyperparameter grid to search over
param_grid = {'C': [0.001, 0.01, 0.1, 1, 10, 100],
              'penalty': ['l1', 'l2']}

# Perform grid search with 5-fold cross-validation
grid_search_LR = GridSearchCV(lr, param_grid, cv=5)
grid_search_LR.fit(X_train_cnn, Y_train)

# Print the best hyperparameters and the corresponding accuracy score
print("Best hyperparameters: ", grid_search_LR.best_params_)
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,
/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,
/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/model_selection/_validation.py:372: FitFai
ledWarning:
30 fits failed out of a total of 60.
The score on these train-test partitions for these parameters will be set to nan.
If these failures are not expected, you can try to debug them by setting error_score='rai
se'.

Below are more details about the failures:
--------------------------------------------------------------------------------
30 fits failed with the following error:
Traceback (most recent call last):
  File "/opt/conda/lib/python3.7/site-packages/sklearn/model_selection/_validation.py", l
ine 680, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "/opt/conda/lib/python3.7/site-packages/sklearn/linear_model/_logistic.py", line 1
461, in fit
    solver = _check_solver(self.solver, self.penalty, self.dual)
  File "/opt/conda/lib/python3.7/site-packages/sklearn/linear_model/_logistic.py", line 4
49, in _check_solver
    % (solver, penalty)
ValueError: Solver lbfgs supports only 'l2' or 'none' penalties, got l1 penalty.
```

```
  warnings.warn(some_fits_failed_message, FitFailedWarning)
/opt/conda/lib/python3.7/site-packages/sklearn/model_selection/_search.py:972: UserWarnin
g: One or more of the test scores are non-finite: [        nan 0.99621788        nan 0.996
37768        nan 0.99637768
        nan 0.99640432        nan 0.99643095        nan 0.99643095]
  category=UserWarning,
```

```
Best hyperparameters:  {'C': 10, 'penalty': 'l2'}
              precision    recall  f1-score   support

       akiec       1.00      1.00      1.00      1359
         bcc       0.99      1.00      1.00      1318
         bkl       0.97      0.99      0.98      1262
          df       1.00      1.00      1.00      1351
          nv       0.98      0.92      0.95      1374
        vasc       1.00      1.00      1.00      1358
         mel       0.96      0.99      0.97      1365

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

Accuracy: 98.51922872057101
```

```
/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 [ ]:

In [ ]: