In [2]:

```
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
```

In [3]:

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

Out[3]:

	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

In [4]:

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

Out[4]:

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

In [5]:

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

In [6]:

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

Out[6]:

```
0
```

In [7]:

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

Out[7]:

	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

	lesion_id	image_id	dx	dx_type	age	sex	localization
3	HAM_0002730	ISIC_0025661	bkl	histo	80.0	male	scalp
4	HAM_0001466	ISIC_0031633	bkl	histo	75.0	male	ear

In [8]:

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

Out[8]:

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

In [9]:

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

In [10]:

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

Out[10]:

```
0
```

In [11]:

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

Out[11]:

	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 [12]:

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

Out[12]:

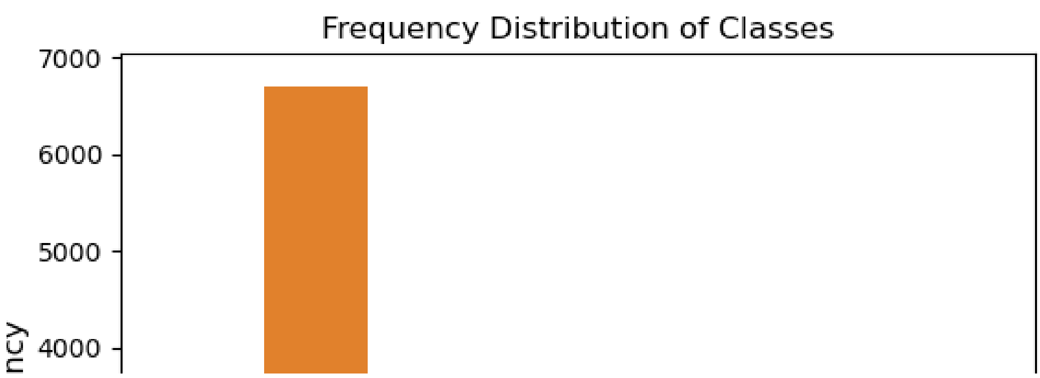
```
array(['bkl', 'nv', 'df', 'mel', 'vasc', 'bcc', 'akiec'], dtype=object)
```

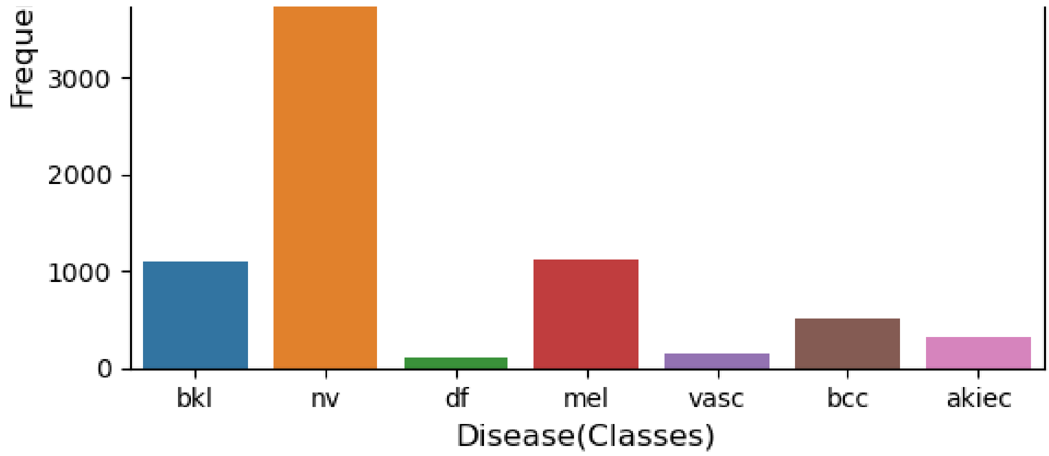
In [13]:

```
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[13]:

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





In [14]:

```
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 [15]:

```
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 [16]:

```
# 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 [17]:

```
# 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 [18]:

```
model_CNN = Sequential()
model_CNN.add(Conv2D(16, kernel_size = (3,3), input_shape = (28, 28, 3), activation = 'r
elu', padding = 'same'))
model_CNN.add(MaxPool2D(pool_size = (2,2)))

model_CNN.add(Conv2D(32, kernel_size = (3,3), activation = 'relu', padding = 'same'))
model_CNN.add(MaxPool2D(pool_size = (2,2), padding = 'same'))

model_CNN.add(Conv2D(64, kernel_size = (3,3), activation = 'relu', padding = 'same'))
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(MaxPool2D(pool_size = (2,2), padding = 'same'))

model_CNN.add(Flatten())
model_CNN.add(Dense(64, activation = 'relu'))
model_CNN.add(Dense(32))
model_CNN.add(Activation(activation='relu'))
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, 16)        448

 max_pooling2d (MaxPooling2D  (None, 14, 14, 16)       0
 )

 conv2d_1 (Conv2D)           (None, 14, 14, 32)        4640

 max_pooling2d_1 (MaxPooling  (None, 7, 7, 32)         0
 2D)

 conv2d_2 (Conv2D)           (None, 7, 7, 64)          18496

 max_pooling2d_2 (MaxPooling  (None, 4, 4, 64)         0
 2D)

 conv2d_3 (Conv2D)           (None, 4, 4, 128)         73856

 max_pooling2d_3 (MaxPooling  (None, 2, 2, 128)        0
 2D)

 flatten (Flatten)           (None, 512)               0

 dense (Dense)               (None, 64)                32832

 dense_1 (Dense)             (None, 32)                2080

 activation (Activation)     (None, 32)                0

 dense_2 (Dense)             (None, 7)                 231

 activation_1 (Activation)   (None, 7)                 0

=================================================================
Total params: 132,583
Trainable params: 132,583
Non-trainable params: 0
_________________________________________________________________
None
```

In [19]:

```
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 [==============================] - 11s 7ms/step - loss: 1.5439 - accuracy: 0.4495
- val_loss: 0.9909 - val_accuracy: 0.6160 - lr: 0.0010
Epoch 2/50
470/470 [==============================] - 3s 7ms/step - loss: 0.8075 - accuracy: 0.6954
- val_loss: 0.6681 - val_accuracy: 0.7455 - lr: 0.0010
Epoch 3/50
470/470 [==============================] - 3s 6ms/step - loss: 0.5480 - accuracy: 0.7950
- val_loss: 0.4580 - val_accuracy: 0.8229 - lr: 0.0010
Epoch 4/50
470/470 [==============================] - 3s 7ms/step - loss: 0.3927 - accuracy: 0.8528
- val_loss: 0.4805 - val_accuracy: 0.8229 - lr: 0.0010
Epoch 5/50
470/470 [==============================] - 3s 6ms/step - loss: 0.3179 - accuracy: 0.8828
- val_loss: 0.3661 - val_accuracy: 0.8638 - lr: 0.0010
Epoch 6/50
470/470 [==============================] - 3s 6ms/step - loss: 0.2621 - accuracy: 0.9038
- val_loss: 0.2403 - val_accuracy: 0.9129 - lr: 0.0010
Epoch 7/50
470/470 [==============================] - 3s 6ms/step - loss: 0.2084 - accuracy: 0.9229
- val_loss: 0.2247 - val_accuracy: 0.9185 - lr: 0.0010
Epoch 8/50
470/470 [==============================] - 3s 6ms/step - loss: 0.1949 - accuracy: 0.9288
- val_loss: 0.2296 - val_accuracy: 0.9190 - lr: 0.0010
Epoch 9/50
470/470 [==============================] - 3s 6ms/step - loss: 0.1832 - accuracy: 0.9337
- val_loss: 0.2104 - val_accuracy: 0.9274 - lr: 0.0010
Epoch 10/50
470/470 [==============================] - 3s 6ms/step - loss: 0.1653 - accuracy: 0.9412
- val_loss: 0.2971 - val_accuracy: 0.9113 - lr: 0.0010
Epoch 11/50
470/470 [==============================] - 3s 6ms/step - loss: 0.1587 - accuracy: 0.9438
- val_loss: 0.1348 - val_accuracy: 0.9547 - lr: 0.0010
Epoch 12/50
470/470 [==============================] - 3s 6ms/step - loss: 0.1409 - accuracy: 0.9498
- val_loss: 0.1849 - val_accuracy: 0.9337 - lr: 0.0010
Epoch 13/50
470/470 [==============================] - 3s 6ms/step - loss: 0.1100 - accuracy: 0.9607
- val_loss: 0.1329 - val_accuracy: 0.9594 - lr: 0.0010
Epoch 14/50
470/470 [==============================] - 3s 6ms/step - loss: 0.1066 - accuracy: 0.9621
- val_loss: 0.1350 - val_accuracy: 0.9553 - lr: 0.0010
Epoch 15/50
470/470 [==============================] - 3s 6ms/step - loss: 0.1117 - accuracy: 0.9614
- val_loss: 0.1987 - val_accuracy: 0.9325 - lr: 0.0010
Epoch 16/50
466/470 [============================>.] - ETA: 0s - loss: 0.1239 - accuracy: 0.9570
Epoch 16: ReduceLROnPlateau reducing learning rate to 0.00010000000474974513.
470/470 [==============================] - 3s 6ms/step - loss: 0.1241 - accuracy: 0.9570
- val_loss: 0.1929 - val_accuracy: 0.9379 - lr: 0.0010
Epoch 17/50
470/470 [==============================] - 3s 6ms/step - loss: 0.0295 - accuracy: 0.9912
- val_loss: 0.0916 - val_accuracy: 0.9752 - lr: 1.0000e-04
Epoch 18/50
470/470 [==============================] - 3s 6ms/step - loss: 0.0144 - accuracy: 0.9967
- val_loss: 0.0867 - val_accuracy: 0.9778 - lr: 1.0000e-04
Epoch 19/50
470/470 [==============================] - 3s 6ms/step - loss: 0.0095 - accuracy: 0.9983
- val_loss: 0.0876 - val_accuracy: 0.9784 - lr: 1.0000e-04
Epoch 20/50
470/470 [==============================] - 3s 6ms/step - loss: 0.0066 - accuracy: 0.9991
- val_loss: 0.0889 - val_accuracy: 0.9784 - lr: 1.0000e-04
Epoch 21/50
466/470 [============================>.] - ETA: 0s - loss: 0.0046 - accuracy: 0.9997
Epoch 21: ReduceLROnPlateau reducing learning rate to 1.0000000474974514e-05.
470/470 [==============================] - 3s 6ms/step - loss: 0.0046 - accuracy: 0.9997
- val_loss: 0.0931 - val_accuracy: 0.9790 - lr: 1.0000e-04
Epoch 22/50
470/470 [==============================] - 3s 6ms/step - loss: 0.0032 - accuracy: 0.9999
- val_loss: 0.0920 - val_accuracy: 0.9794 - lr: 1.0000e-05
Epoch 23/50
```

```
470/470 [==============================] - 3s 6ms/step - loss: 0.0030 - accuracy: 0.9999
- val_loss: 0.0917 - val_accuracy: 0.9795 - lr: 1.0000e-05
Epoch 24/50
468/470 [============================>.] - ETA: 0s - loss: 0.0029 - accuracy: 0.9999
Epoch 24: ReduceLROnPlateau reducing learning rate to 1.0000000656873453e-06.
470/470 [==============================] - 3s 7ms/step - loss: 0.0029 - accuracy: 0.9999
- val_loss: 0.0916 - val_accuracy: 0.9796 - lr: 1.0000e-05
Epoch 25/50
470/470 [==============================] - 3s 6ms/step - loss: 0.0027 - accuracy: 0.9999
- val_loss: 0.0920 - val_accuracy: 0.9796 - lr: 1.0000e-06
Epoch 26/50
470/470 [==============================] - 3s 6ms/step - loss: 0.0027 - accuracy: 0.9999
- val_loss: 0.0925 - val_accuracy: 0.9794 - lr: 1.0000e-06
Epoch 27/50
463/470 [============================>.] - ETA: 0s - loss: 0.0027 - accuracy: 0.9999
Epoch 27: ReduceLROnPlateau reducing learning rate to 1.0000001111620805e-07.
470/470 [==============================] - 3s 6ms/step - loss: 0.0027 - accuracy: 0.9999
- val_loss: 0.0926 - val_accuracy: 0.9795 - lr: 1.0000e-06
Epoch 28/50
470/470 [==============================] - 3s 6ms/step - loss: 0.0026 - accuracy: 0.9999
- val_loss: 0.0926 - val_accuracy: 0.9794 - lr: 1.0000e-07
Epoch 28: early stopping
```

In [20]:

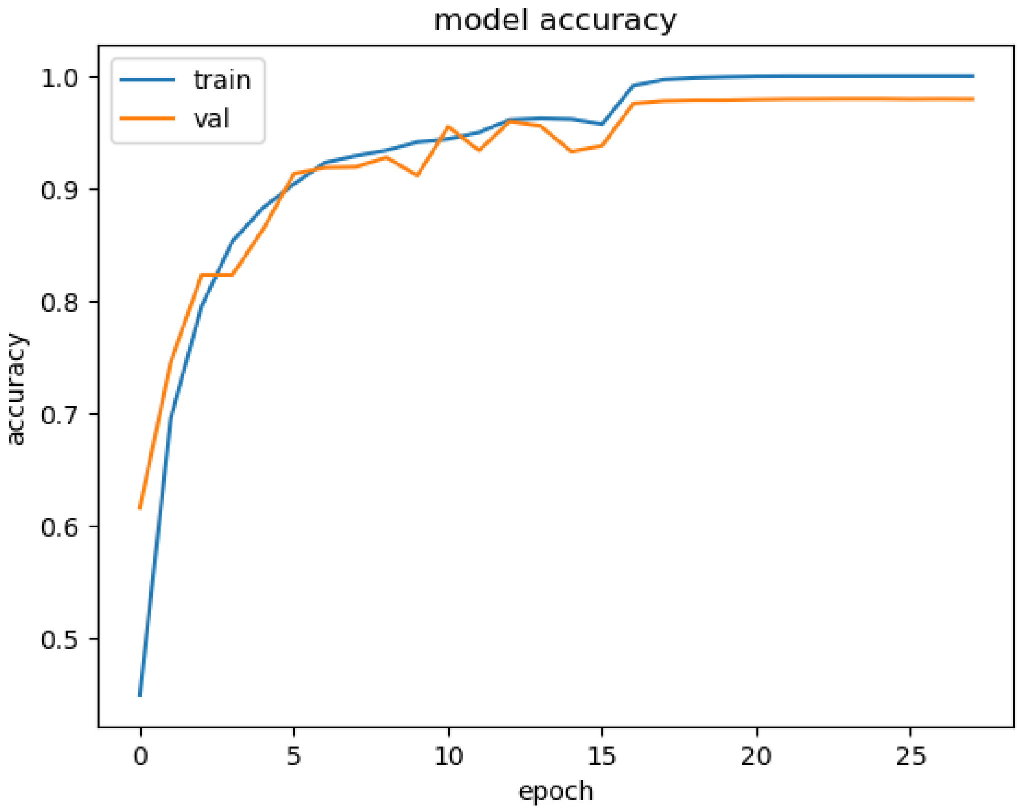
```python
results = model_CNN.evaluate(X_test , Y_test, verbose=0)

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

```
    Test Loss: 0.09621
Test Accuracy: 97.82%
```

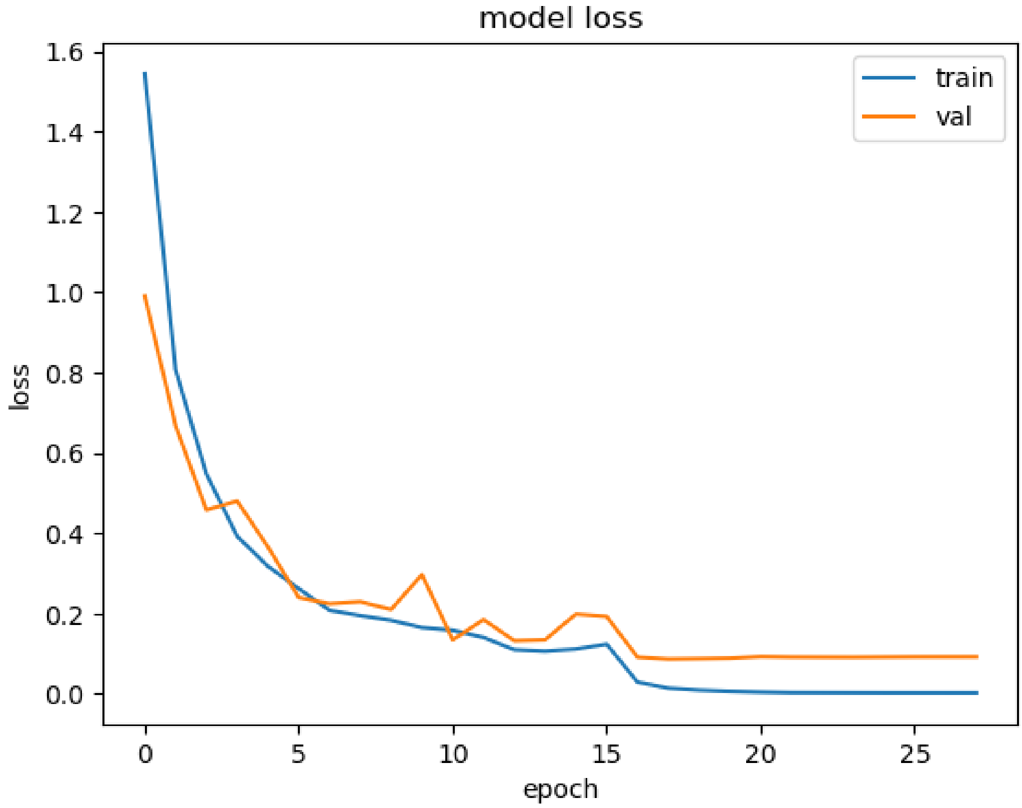
In [21]:

```python
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 [22]:

```
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 [23]:

```
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('Y Actual Values :' , y_true_CNN[0:10])
print('Y Predicted Values :' , y_pred_CNN[0:10])
```

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

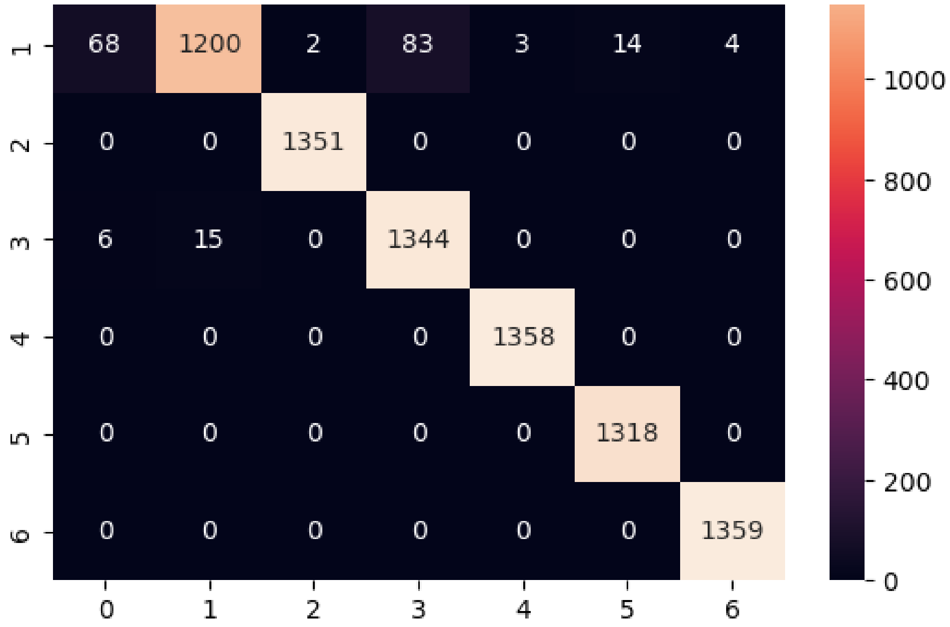
In [24]:

```
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='')
```

```
[[1252    1    0    1    1    4    3]
 [  68 1200    2   83    3   14    4]
 [   0    0 1351    0    0    0    0]
 [   6   15    0 1344    0    0    0]
 [   0    0    0    0 1358    0    0]
 [   0    0    0    0    0 1318    0]
 [   0    0    0    0    0    0 1359]]
```

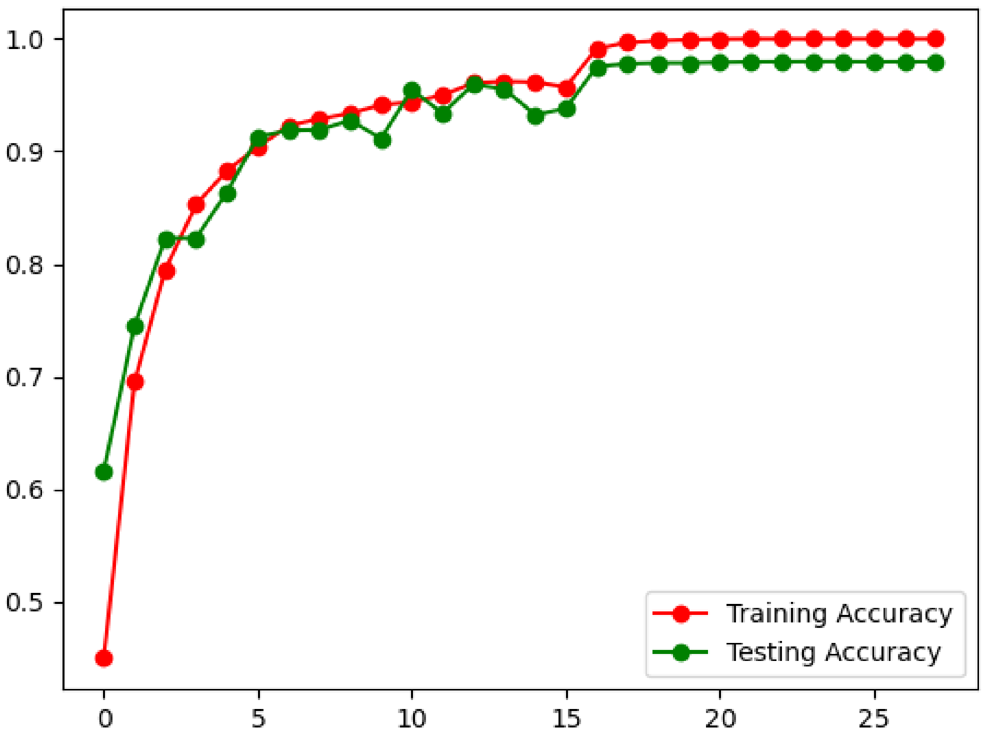
Out[24]:

<AxesSubplot:>



In [25]:

```
#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 [26]:

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

```
294/294 [==============================] - 1s 2ms/step
9387    9387
              precision    recall  f1-score   support

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

```
          nv       0.99      0.87      0.93      1374
        vasc       1.00      1.00      1.00      1358
         mel       0.94      0.98      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 [27]:

```
# 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 0x7fd095ac7a90>
1 <keras.layers.pooling.max_pooling2d.MaxPooling2D object at 0x7fd0ffd3d5d0>
2 <keras.layers.convolutional.conv2d.Conv2D object at 0x7fd0ffd3d4d0>
3 <keras.layers.pooling.max_pooling2d.MaxPooling2D object at 0x7fd091448210>
4 <keras.layers.convolutional.conv2d.Conv2D object at 0x7fd0914608d0>
5 <keras.layers.pooling.max_pooling2d.MaxPooling2D object at 0x7fd0ffbd2190>
6 <keras.layers.convolutional.conv2d.Conv2D object at 0x7fd091457790>
7 <keras.layers.pooling.max_pooling2d.MaxPooling2D object at 0x7fd09144dd10>
8 <keras.layers.reshaping.flatten.Flatten object at 0x7fd09142c210>
9 <keras.layers.core.dense.Dense object at 0x7fd0ffab7850>
10 <keras.layers.core.dense.Dense object at 0x7fd0ffafae10>
11 <keras.layers.core.activation.Activation object at 0x7fd09144d790>
12 <keras.layers.core.dense.Dense object at 0x7fd091448890>
13 <keras.layers.core.activation.Activation object at 0x7fd0ffb3e590>
```

In [28]:

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

```
tensorflow
```

In [29]:

```
import tensorflow as tf
feature_extractor = tf.keras.Model(inputs=model_CNN.input,
                                    outputs=model_CNN.get_layer('activation').output)
output_layers_model =tf.keras.Model(inputs=model_CNN.input, outputs=model_CNN.output)
```

In [30]:

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

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

In [38]:

```
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)
```

```
SVM Accuracy: 98.13571961222968
```

SVM Accuracy: 98.13571961222968

In [66]:

```
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)
```

```
SVM Accuracy: 98.13571961222968
SVC(C=1000, gamma=0.001)
```

Out[66]:

```
SVC(C=1000, gamma=0.001)
```

In [68]:

```
y_testSVM = svmclf.predict(X_test_cnn)
from sklearn.metrics import confusion_matrix, classification_report, accuracy_score

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

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      1359
           1       0.99      1.00      0.99      1318
           2       0.95      0.99      0.97      1262
           3       1.00      1.00      1.00      1351
           4       0.99      0.90      0.94      1374
           5       1.00      1.00      1.00      1358
           6       0.95      0.98      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

Accuracy: 98.13571961222968
```

In [64]:

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

parameters = {"max_depth": [3],
              "max_features": [1],
              "min_samples_split": [3],
              "min_samples_leaf": [3],
              "bootstrap": [True],
              "criterion": ["entropy"],
              "n_estimators": [10]}
rclf = RandomForestClassifier()
rgclf = GridSearchCV(rclf, param_grid=parameters)
rgclf.fit(X_test_cnn, Y_test)
RFC_accuracy = clf.score(X_test_cnn, Y_test)
print('Random Forest Classifier Accuracy:', RFC_accuracy*100)
```

```
Random Forest Classifier Accuracy: 98.13571961222968
```

In [71]:

```
RFclf = rgclf.best_estimator_
RFclf.fit(X_test_cnn, Y_test)
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))
print("Accuracy: {0}".format(accuracy_score(Y_test, y_testRFC)*100))
```

```
RandomForestClassifier(criterion='entropy', max_depth=3, max_features=1,
```

```
                        min_samples_leaf=3, min_samples_split=3,
                        n_estimators=10)
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      1359
           1       0.99      1.00      1.00      1318
           2       0.97      0.99      0.98      1262
           3       1.00      1.00      1.00      1351
           4       0.97      0.93      0.95      1374
           5       1.00      1.00      1.00      1358
           6       0.97      0.98      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
```

In [72]:

```
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_test_cnn, Y_test)
KNN_accuracy = kgclf.score(X_test_cnn, Y_test)
print('KNN Classifier Accuracy:', KNN_accuracy*100)
```

```
KNN Classifier Accuracy: 100.0
```

In [73]:

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

```
KNeighborsClassifier(n_neighbors=30, weights='distance')
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      1359
           1       1.00      1.00      1.00      1318
           2       1.00      1.00      1.00      1262
           3       1.00      1.00      1.00      1351
           4       1.00      1.00      1.00      1374
           5       1.00      1.00      1.00      1358
           6       1.00      1.00      1.00      1365

    accuracy                           1.00      9387
   macro avg       1.00      1.00      1.00      9387
weighted avg       1.00      1.00      1.00      9387

Accuracy: 100.0
```

In [77]:

```
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
```

```python
# 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_test_cnn, Y_test)

# Print the best hyperparameters and the corresponding accuracy score
print("Best hyperparameters: ", grid_search_LR.best_params_)
y_testKNN = grid_search_LR.predict(X_test_cnn)

print(classification_report(Y_test, y_testKNN))
print("Accuracy: {0}".format(accuracy_score(Y_test, y_testKNN)*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
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  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG,
/opt/conda/lib/python3.7/site-packages/sklearn/linear_model/_logistic.py:818: Convergence
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    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
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  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.

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    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 0.97837456        nan 0.978
80066        nan 0.98007913
        nan 0.98114426        nan 0.98189002        nan 0.98220956]
  category=UserWarning,
```

```
Best hyperparameters:  {'C': 100, 'penalty': 'l2'}
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      1359
           1       0.99      1.00      0.99      1318
           2       0.96      0.99      0.97      1262
           3       1.00      1.00      1.00      1351
           4       0.98      0.91      0.94      1374
```

```
           5       1.00      1.00      1.00      1358
           6       0.95      0.98      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

Accuracy: 98.25290295088953
```

```
/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 [ ]: