

In [6]:

```
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
```

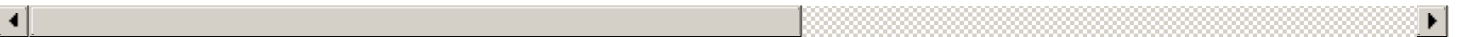
In [7]:

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

Out[7]:

	pixel0000	pixel0001	pixel0002	pixel0003	pixel0004	pixel0005	pixel0006	pixel0007	pixel0008	pixel0009	...	pixel2343	pixel2344
0	192	153	193	195	155	192	197	154	185	202	...	173	174
1	25	14	30	68	48	75	123	93	126	158	...	60	61
2	192	138	153	200	145	163	201	142	160	206	...	167	168
3	38	19	30	95	59	72	143	103	119	171	...	44	45
4	158	113	139	194	144	174	215	162	191	225	...	209	210

5 rows × 2353 columns



In [9]:

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

Out[9]:

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

In [10]:

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

In [11]:

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

Out[11]:

```
0
```

In [12]:

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

Out[12]:

	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_0025664	bkl	histo	80.0	male	scalp

	lesion_id	image_id	dx	dx_type	age	sex	localization
3	HAM_0002730	ISIC_0023001	bkl	histo	60.0	male	scalp
4	HAM_0001466	ISIC_0031633	bkl	histo	75.0	male	ear

In [13]:

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

Out[13]:

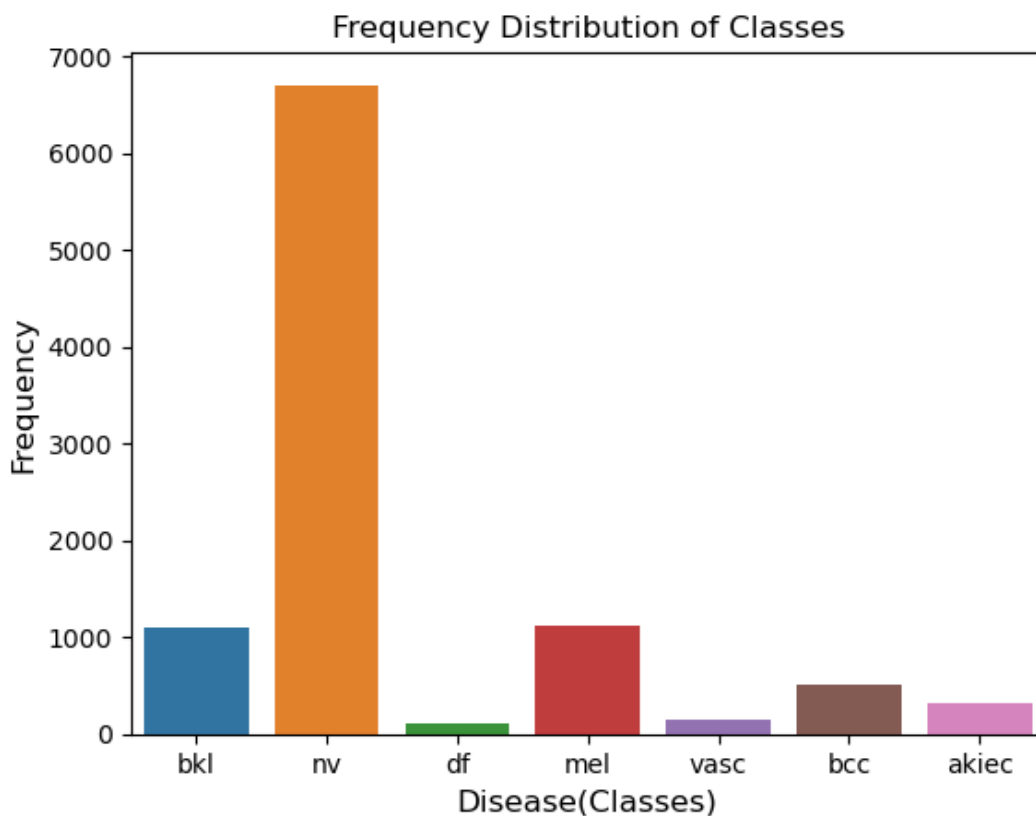
```
array(['bkl', 'nv', 'df', 'mel', 'vasc', 'bcc', 'akiec'], dtype=object)
```

In [14]:

```
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[14]:

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



In [15]:

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

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

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

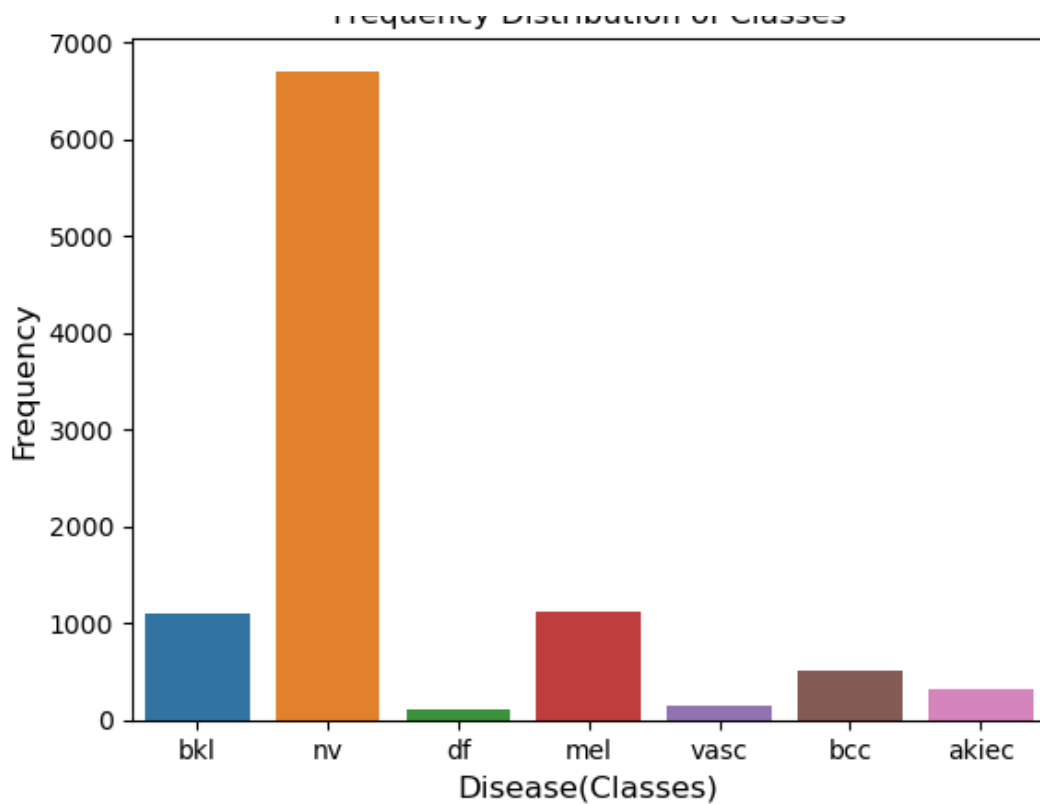
In [176]:

```
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[176]:

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

Frequency Distribution of Classes



In []:

In [32]:

```
# reshaping the data so that it can be taken by convolution neural network(without disturbing 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 [33]:

```
# 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 = Sequential()

model.add(Conv2D(16, kernel_size = (3,3), input_shape = (28, 28, 3), activation = 'relu'))
model.add(Conv2D(32, kernel_size = (3,3), activation = 'relu'))
model.add(MaxPool2D(pool_size = (2,2)))

model.add(Conv2D(32, kernel_size = (3,3), activation = 'relu'))
model.add(Conv2D(64, kernel_size = (3,3), activation = 'relu'))
model.add(MaxPool2D(pool_size = (2,2)))

model.add(Flatten())
model.add(Dense(64, activation='relu'))
model.add(Dense(7, activation='softmax'))
model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 26, 26, 16)	448
conv2d_1 (Conv2D)	(None, 24, 24, 32)	4640
max_pooling2d (MaxPooling2D)	(None, 12, 12, 32)	0
conv2d_2 (Conv2D)	(None, 10, 10, 32)	9248
conv2d_3 (Conv2D)	(None, 8, 8, 64)	18496
max_pooling2d_1 (MaxPooling2D)	(None, 4, 4, 64)	0
flatten (Flatten)	(None, 1024)	0
dense (Dense)	(None, 64)	65600
dense_1 (Dense)	(None, 7)	455

Total params: 98,887
 Trainable params: 98,887
 Non-trainable params: 0

In [19]:

```

model.compile(loss = 'sparse_categorical_crossentropy',
              optimizer = 'adam',
              metrics = ['accuracy'])
history = model.fit(X_train,
                    Y_train,
                    validation_split=0.2,
                    batch_size = 128,
                    epochs = 50)

```

```

Epoch 1/50
235/235 [=====] - 27s 108ms/step - loss: 2.2407 - accuracy: 0.42
00 - val_loss: 1.1698 - val_accuracy: 0.5382
Epoch 2/50
235/235 [=====] - 25s 106ms/step - loss: 0.9816 - accuracy: 0.62
96 - val_loss: 0.8212 - val_accuracy: 0.6968
Epoch 3/50
235/235 [=====] - 25s 105ms/step - loss: 0.7226 - accuracy: 0.73
48 - val_loss: 0.6027 - val_accuracy: 0.7881
Epoch 4/50
235/235 [=====] - 24s 103ms/step - loss: 0.5639 - accuracy: 0.79
94 - val_loss: 0.5137 - val_accuracy: 0.8212
Epoch 5/50
235/235 [=====] - 24s 104ms/step - loss: 0.4348 - accuracy: 0.84
91 - val_loss: 0.4219 - val_accuracy: 0.8565
Epoch 6/50
235/235 [=====] - 25s 105ms/step - loss: 0.3399 - accuracy: 0.88
34 - val_loss: 0.3213 - val_accuracy: 0.8963
Epoch 7/50
235/235 [=====] - 25s 105ms/step - loss: 0.2770 - accuracy: 0.90
62 - val_loss: 0.3263 - val_accuracy: 0.8991
Epoch 8/50
235/235 [=====] - 24s 103ms/step - loss: 0.2200 - accuracy: 0.92
70 - val_loss: 0.2835 - val_accuracy: 0.9035
Epoch 9/50
235/235 [=====] - 25s 105ms/step - loss: 0.1927 - accuracy: 0.93
53 - val_loss: 0.3118 - val_accuracy: 0.8943
Epoch 10/50
235/235 [=====] - 25s 104ms/step - loss: 0.1705 - accuracy: 0.94
32 - val_loss: 0.2698 - val_accuracy: 0.9158
Epoch 11/50
235/235 [=====] - 25s 105ms/step - loss: 0.1648 - accuracy: 0.94
34 - val_loss: 0.1969 - val_accuracy: 0.9425

```

Epoch 12/50
235/235 [=====] - 24s 104ms/step - loss: 0.1233 - accuracy: 0.95
81 - val_loss: 0.2373 - val_accuracy: 0.9294

Epoch 13/50
235/235 [=====] - 26s 110ms/step - loss: 0.1073 - accuracy: 0.96
31 - val_loss: 0.1820 - val_accuracy: 0.9463

Epoch 14/50
235/235 [=====] - 25s 105ms/step - loss: 0.1016 - accuracy: 0.96
56 - val_loss: 0.1913 - val_accuracy: 0.9490

Epoch 15/50
235/235 [=====] - 25s 106ms/step - loss: 0.1078 - accuracy: 0.96
27 - val_loss: 0.2291 - val_accuracy: 0.9372

Epoch 16/50
235/235 [=====] - 25s 106ms/step - loss: 0.1148 - accuracy: 0.95
97 - val_loss: 0.2536 - val_accuracy: 0.9205

Epoch 17/50
235/235 [=====] - 24s 104ms/step - loss: 0.0866 - accuracy: 0.97
03 - val_loss: 0.1994 - val_accuracy: 0.9535

Epoch 18/50
235/235 [=====] - 25s 106ms/step - loss: 0.0672 - accuracy: 0.97
74 - val_loss: 0.2455 - val_accuracy: 0.9242

Epoch 19/50
235/235 [=====] - 25s 105ms/step - loss: 0.1038 - accuracy: 0.96
32 - val_loss: 0.2551 - val_accuracy: 0.9317

Epoch 20/50
235/235 [=====] - 25s 105ms/step - loss: 0.0945 - accuracy: 0.96
78 - val_loss: 0.1941 - val_accuracy: 0.9551

Epoch 21/50
235/235 [=====] - 24s 103ms/step - loss: 0.0927 - accuracy: 0.96
81 - val_loss: 0.2799 - val_accuracy: 0.9370

Epoch 22/50
235/235 [=====] - 24s 104ms/step - loss: 0.0723 - accuracy: 0.97
59 - val_loss: 0.2433 - val_accuracy: 0.9453

Epoch 23/50
235/235 [=====] - 25s 104ms/step - loss: 0.1083 - accuracy: 0.96
27 - val_loss: 0.2846 - val_accuracy: 0.9397

Epoch 24/50
235/235 [=====] - 25s 105ms/step - loss: 0.0428 - accuracy: 0.98
56 - val_loss: 0.1760 - val_accuracy: 0.9648

Epoch 25/50
235/235 [=====] - 24s 103ms/step - loss: 0.0564 - accuracy: 0.98
03 - val_loss: 0.2706 - val_accuracy: 0.9409

Epoch 26/50
235/235 [=====] - 25s 105ms/step - loss: 0.0557 - accuracy: 0.98
09 - val_loss: 0.1837 - val_accuracy: 0.9591

Epoch 27/50
235/235 [=====] - 25s 105ms/step - loss: 0.0481 - accuracy: 0.98
39 - val_loss: 0.2371 - val_accuracy: 0.9402

Epoch 28/50
235/235 [=====] - 25s 106ms/step - loss: 0.1195 - accuracy: 0.96
23 - val_loss: 0.2985 - val_accuracy: 0.9205

Epoch 29/50
235/235 [=====] - 25s 104ms/step - loss: 0.0661 - accuracy: 0.97
90 - val_loss: 0.1858 - val_accuracy: 0.9663

Epoch 30/50
235/235 [=====] - 24s 103ms/step - loss: 0.0163 - accuracy: 0.99
47 - val_loss: 0.1853 - val_accuracy: 0.9682

Epoch 31/50
235/235 [=====] - 25s 104ms/step - loss: 0.0617 - accuracy: 0.98
01 - val_loss: 0.2936 - val_accuracy: 0.9276

Epoch 32/50
235/235 [=====] - 25s 104ms/step - loss: 0.0806 - accuracy: 0.97
46 - val_loss: 0.2099 - val_accuracy: 0.9586

Epoch 33/50
235/235 [=====] - 25s 104ms/step - loss: 0.0478 - accuracy: 0.98
38 - val_loss: 0.1715 - val_accuracy: 0.9652

Epoch 34/50
235/235 [=====] - 24s 103ms/step - loss: 0.0452 - accuracy: 0.98
46 - val_loss: 0.4645 - val_accuracy: 0.9008

Epoch 35/50
235/235 [=====] - 25s 105ms/step - loss: 0.0833 - accuracy: 0.97
35 - val_loss: 0.1911 - val_accuracy: 0.9659

```

Epoch 36/50
235/235 [=====] - 24s 104ms/step - loss: 0.0314 - accuracy: 0.98
91 - val_loss: 0.1458 - val_accuracy: 0.9736
Epoch 37/50
235/235 [=====] - 25s 104ms/step - loss: 0.0642 - accuracy: 0.97
98 - val_loss: 0.3125 - val_accuracy: 0.9342
Epoch 38/50
235/235 [=====] - 24s 103ms/step - loss: 0.0683 - accuracy: 0.97
85 - val_loss: 0.2829 - val_accuracy: 0.9382
Epoch 39/50
235/235 [=====] - 25s 104ms/step - loss: 0.0346 - accuracy: 0.98
87 - val_loss: 0.2152 - val_accuracy: 0.9650
Epoch 40/50
235/235 [=====] - 24s 104ms/step - loss: 0.0460 - accuracy: 0.98
59 - val_loss: 0.3936 - val_accuracy: 0.9293
Epoch 41/50
235/235 [=====] - 25s 105ms/step - loss: 0.0846 - accuracy: 0.97
39 - val_loss: 0.2402 - val_accuracy: 0.9527
Epoch 42/50
235/235 [=====] - 24s 102ms/step - loss: 0.0421 - accuracy: 0.98
71 - val_loss: 0.2066 - val_accuracy: 0.9663
Epoch 43/50
235/235 [=====] - 24s 103ms/step - loss: 0.0082 - accuracy: 0.99
76 - val_loss: 0.1750 - val_accuracy: 0.9747
Epoch 44/50
235/235 [=====] - 24s 104ms/step - loss: 0.0014 - accuracy: 0.99
98 - val_loss: 0.1577 - val_accuracy: 0.9775
Epoch 45/50
235/235 [=====] - 25s 105ms/step - loss: 6.0696e-04 - accuracy:
1.0000 - val_loss: 0.1758 - val_accuracy: 0.9762
Epoch 46/50
235/235 [=====] - 24s 104ms/step - loss: 2.2905e-04 - accuracy:
1.0000 - val_loss: 0.1793 - val_accuracy: 0.9764
Epoch 47/50
235/235 [=====] - 24s 104ms/step - loss: 1.7136e-04 - accuracy:
1.0000 - val_loss: 0.1845 - val_accuracy: 0.9768
Epoch 48/50
235/235 [=====] - 24s 104ms/step - loss: 1.3468e-04 - accuracy:
1.0000 - val_loss: 0.1942 - val_accuracy: 0.9764
Epoch 49/50
235/235 [=====] - 24s 104ms/step - loss: 1.1190e-04 - accuracy:
1.0000 - val_loss: 0.1918 - val_accuracy: 0.9770
Epoch 50/50
235/235 [=====] - 25s 105ms/step - loss: 9.4261e-05 - accuracy:
1.0000 - val_loss: 0.1981 - val_accuracy: 0.9763

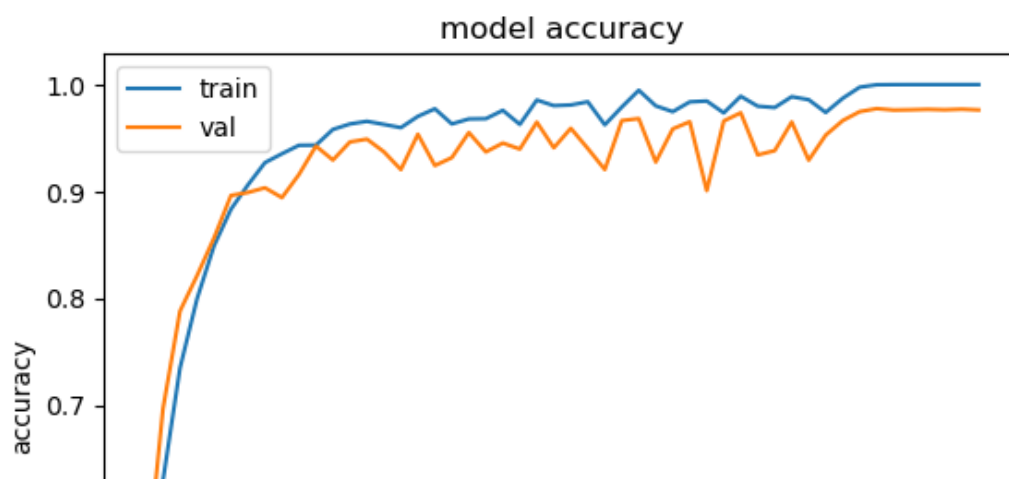
```

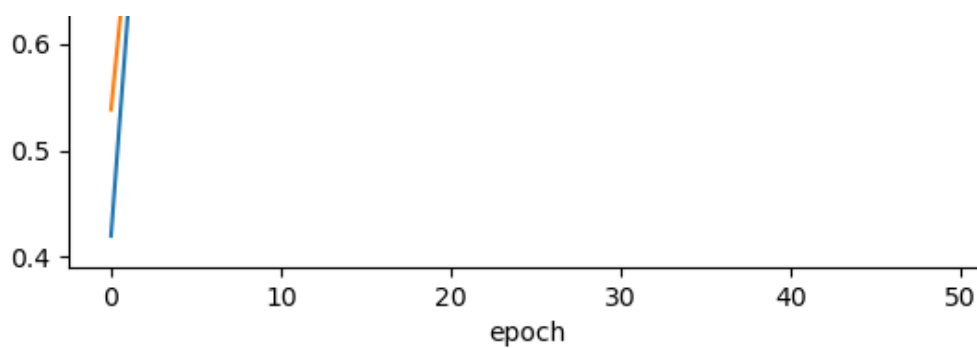
In [34]:

```

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()

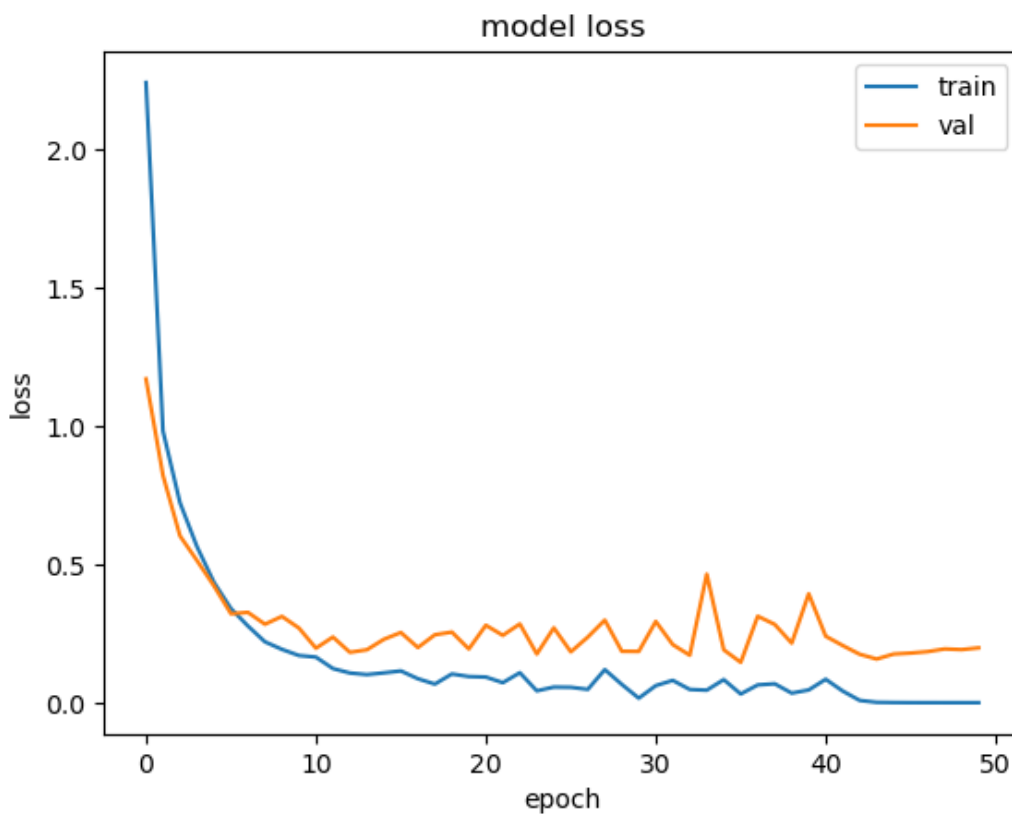
```





In [35]:

```
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 [36]:

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

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

```
    Test Loss: 0.17264
Test Accuracy: 97.62%
```

In [37]:

```
from sklearn.metrics import confusion_matrix , classification_report

y_true = list(Y_test)
y_pred = model.predict(X_test)
y_pred = list(map(lambda x: np.argmax(x), y_pred))
print('Y Actual Values :', y_true[0:10])
print('Y Predicted Values :', y_pred[0:10])
```

```
294/294 [=====] - 3s 9ms/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 [38]:

```
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 [39]:

```
classes = {4: ('nv', 'melanocytic nevi'),
             6: ('mel', 'melanoma'),
             2: ('bkl', 'benign keratosis-like lesions'),
             1: ('bcc', 'basal cell carcinoma'),
             5: ('vasc', 'pyogenic granulomas and hemorrhage'),
             0: ('akiec', 'Actinic keratoses and intraepithelial carcinomae'),
             3: ('df', 'dermatofibroma')}
```

In [40]:

```
cm = confusion_matrix(y_true,y_pred,labels=classes_labels)
print(confusion_matrix(y_true,y_pred,labels=classes_labels))

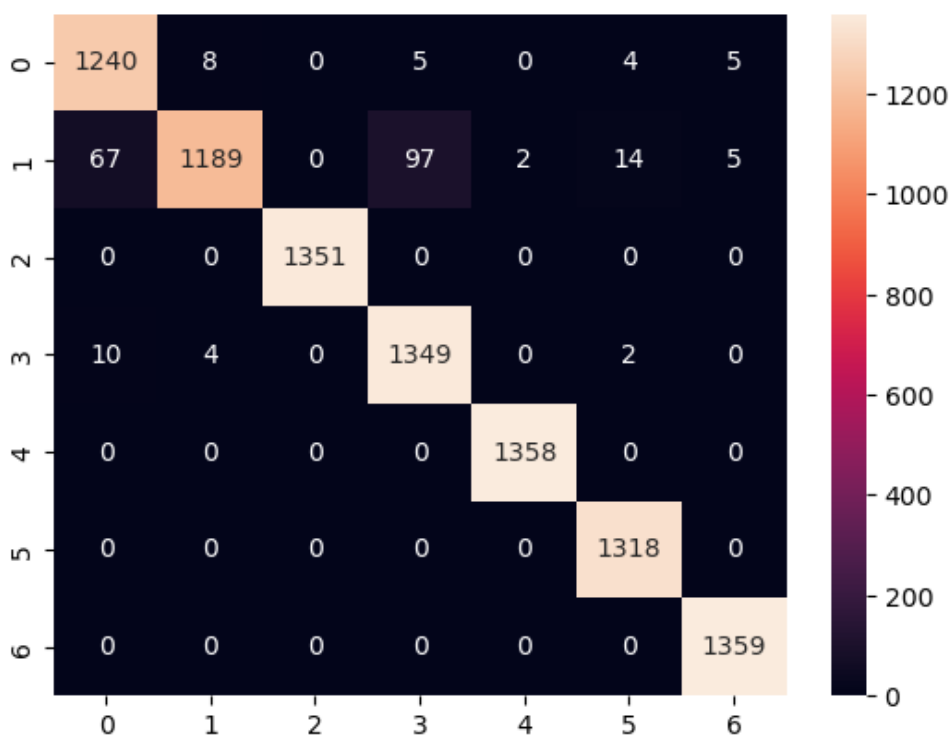
[[1240      8      0      5      0      4      5]
 [   67 1189      0    97      2     14      5]
 [      0      0 1351      0      0      0      0]
 [   10      4      0 1349      0      2      0]
 [      0      0      0      0 1358      0      0]
 [      0      0      0      0      0 1318      0]
 [      0      0      0      0      0      0 1359]]
```

In [41]:

```
sns.heatmap(cm, annot = True, fmt='')
```

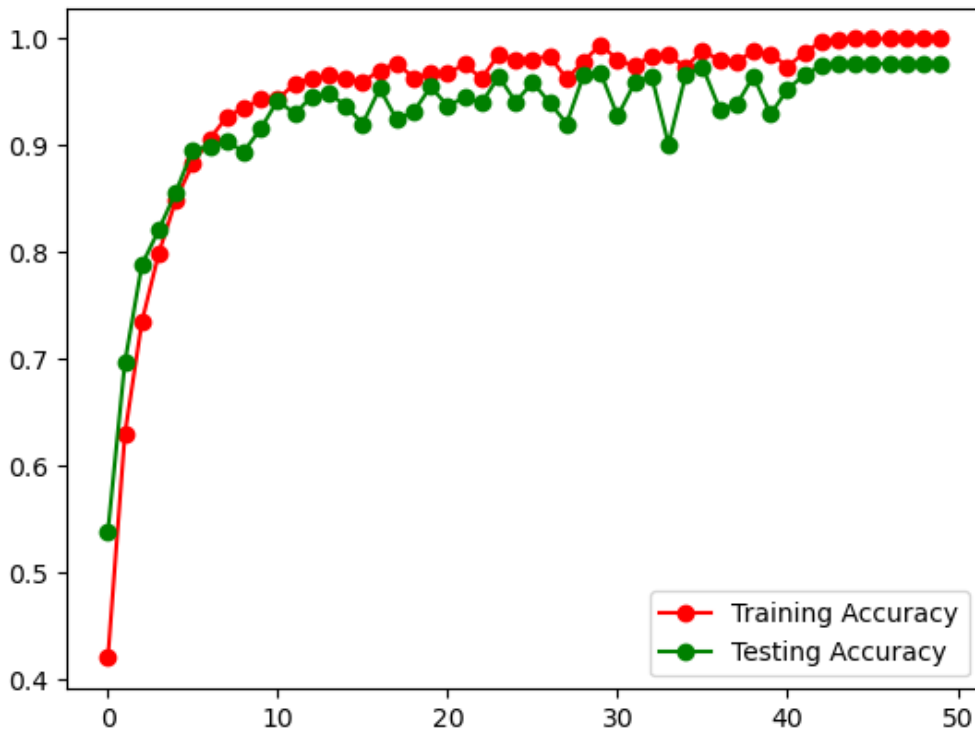
Out[41]:

<AxesSubplot:>



In [42]:


```
#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 [43]:

```
#predicting
y_pred = model.predict(X_test).round()
```

294/294 [=====] - 3s 9ms/step

In [44]:

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

score	support		precision	recall	f1-
0.99	1359	('akiec', 'Actinic keratoses and intraepithelial carcinomae')	0.99	1.00	1
0.99	1318	('bcc', ' basal cell carcinoma')	0.99	1.00	
0.96	1262	('bkl', 'benign keratosis-like lesions')	0.94	0.98	
1.00	1351	('df', 'dermatofibroma')	1.00	1.00	
0.92	1374	('nv', ' melanocytic nevi')	0.99	0.86	
1.00	1358	('vasc', ' pyogenic granulomas and hemorrhage')	1.00	1.00	
0.96	1365	('mel', 'melanoma')	0.93	0.99	
accuracy					
0.98	9387				
0.98	9387	macro avg	0.98	0.98	
0.98	9387	weighted avg	0.98	0.98	

In []:

NEW CNN Model 4-Layers

In [45]:

```
model_CNN = Sequential()
    model_CNN.add(Conv2D(16, kernel_size = (3,3), input_shape = (28, 28, 3), activation
= 'relu', 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, activation='relu'))
    model_CNN.add(Dense(7, 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_4 (Conv2D)	(None, 28, 28, 16)	448
max_pooling2d_2 (MaxPooling 2D)	(None, 14, 14, 16)	0
conv2d_5 (Conv2D)	(None, 14, 14, 32)	4640
max_pooling2d_3 (MaxPooling 2D)	(None, 7, 7, 32)	0
conv2d_6 (Conv2D)	(None, 7, 7, 64)	18496
max_pooling2d_4 (MaxPooling 2D)	(None, 4, 4, 64)	0
conv2d_7 (Conv2D)	(None, 4, 4, 128)	73856
max_pooling2d_5 (MaxPooling 2D)	(None, 2, 2, 128)	0
flatten_1 (Flatten)	(None, 512)	0
dense_2 (Dense)	(None, 64)	32832
dense_3 (Dense)	(None, 32)	2080
dense_4 (Dense)	(None, 7)	231

```
Total params: 132,583
Trainable params: 132,583
Non-trainable params: 0
```

None

In [46]:

```
history = model_CNN.fit(X_train,
                        Y_train,
                        validation_split=0.2,
                        batch_size = 128,
                        epochs = 50)
```

Epoch 1/50

235/235 [=====] - 20s 77ms/step - loss: 2.2062 - accuracy: 0.393
1 - val_loss: 1.1830 - val_accuracy: 0.5507

Epoch 2/50

235/235 [=====] - 17s 74ms/step - loss: 1.0033 - accuracy: 0.619
7 - val_loss: 0.8135 - val_accuracy: 0.7075

Epoch 3/50

235/235 [=====] - 18s 76ms/step - loss: 0.7482 - accuracy: 0.719
5 - val_loss: 0.6418 - val_accuracy: 0.7638

Epoch 4/50

235/235 [=====] - 17s 74ms/step - loss: 0.5512 - accuracy: 0.795
5 - val_loss: 0.4952 - val_accuracy: 0.8189

Epoch 5/50

235/235 [=====] - 18s 76ms/step - loss: 0.4306 - accuracy: 0.841
5 - val_loss: 0.3839 - val_accuracy: 0.8631

Epoch 6/50

235/235 [=====] - 18s 75ms/step - loss: 0.3420 - accuracy: 0.879
1 - val_loss: 0.3941 - val_accuracy: 0.8589

Epoch 7/50

235/235 [=====] - 18s 76ms/step - loss: 0.2749 - accuracy: 0.904
4 - val_loss: 0.2474 - val_accuracy: 0.9152

Epoch 8/50

235/235 [=====] - 18s 77ms/step - loss: 0.2116 - accuracy: 0.926
2 - val_loss: 0.2837 - val_accuracy: 0.8973

Epoch 9/50

235/235 [=====] - 17s 74ms/step - loss: 0.1874 - accuracy: 0.936
3 - val_loss: 0.2229 - val_accuracy: 0.9225

Epoch 10/50

235/235 [=====] - 18s 76ms/step - loss: 0.1893 - accuracy: 0.934
7 - val_loss: 0.2190 - val_accuracy: 0.9314

Epoch 11/50

235/235 [=====] - 18s 75ms/step - loss: 0.1351 - accuracy: 0.954
1 - val_loss: 0.1745 - val_accuracy: 0.9477

Epoch 12/50

235/235 [=====] - 18s 77ms/step - loss: 0.1050 - accuracy: 0.963
8 - val_loss: 0.1714 - val_accuracy: 0.9470

Epoch 13/50

235/235 [=====] - 18s 76ms/step - loss: 0.1151 - accuracy: 0.960
0 - val_loss: 0.2353 - val_accuracy: 0.9270

Epoch 14/50

235/235 [=====] - 18s 77ms/step - loss: 0.1065 - accuracy: 0.962
8 - val_loss: 0.1641 - val_accuracy: 0.9513

Epoch 15/50

235/235 [=====] - 18s 75ms/step - loss: 0.0958 - accuracy: 0.967
0 - val_loss: 0.2381 - val_accuracy: 0.9328

Epoch 16/50

235/235 [=====] - 18s 76ms/step - loss: 0.1240 - accuracy: 0.955
8 - val_loss: 0.1614 - val_accuracy: 0.9551

Epoch 17/50

235/235 [=====] - 18s 75ms/step - loss: 0.1144 - accuracy: 0.960
5 - val_loss: 0.1763 - val_accuracy: 0.9482

Epoch 18/50

235/235 [=====] - 17s 74ms/step - loss: 0.0562 - accuracy: 0.981
4 - val_loss: 0.1244 - val_accuracy: 0.9636

Epoch 19/50

235/235 [=====] - 18s 78ms/step - loss: 0.1079 - accuracy: 0.962
8 - val_loss: 0.1861 - val_accuracy: 0.9473

Epoch 20/50

Epoch 20/50
235/235 [=====] - 18s 76ms/step - loss: 0.0743 - accuracy: 0.972
8 - val_loss: 0.1462 - val_accuracy: 0.9597
Epoch 21/50
235/235 [=====] - 19s 80ms/step - loss: 0.0597 - accuracy: 0.978
8 - val_loss: 0.2509 - val_accuracy: 0.9249
Epoch 22/50
235/235 [=====] - 18s 75ms/step - loss: 0.0640 - accuracy: 0.978
1 - val_loss: 0.2125 - val_accuracy: 0.9419
Epoch 23/50
235/235 [=====] - 18s 78ms/step - loss: 0.1135 - accuracy: 0.962
0 - val_loss: 0.1689 - val_accuracy: 0.9566
Epoch 24/50
235/235 [=====] - 18s 77ms/step - loss: 0.0488 - accuracy: 0.983
5 - val_loss: 0.1719 - val_accuracy: 0.9638
Epoch 25/50
235/235 [=====] - 18s 77ms/step - loss: 0.0399 - accuracy: 0.985
6 - val_loss: 0.2633 - val_accuracy: 0.9268
Epoch 26/50
235/235 [=====] - 18s 78ms/step - loss: 0.1040 - accuracy: 0.966
0 - val_loss: 0.2146 - val_accuracy: 0.9505
Epoch 27/50
235/235 [=====] - 18s 77ms/step - loss: 0.0756 - accuracy: 0.974
6 - val_loss: 0.1280 - val_accuracy: 0.9694
Epoch 28/50
235/235 [=====] - 19s 80ms/step - loss: 0.0166 - accuracy: 0.994
0 - val_loss: 0.1653 - val_accuracy: 0.9691
Epoch 29/50
235/235 [=====] - 18s 77ms/step - loss: 0.0732 - accuracy: 0.974
8 - val_loss: 0.1609 - val_accuracy: 0.9643
Epoch 30/50
235/235 [=====] - 18s 78ms/step - loss: 0.0808 - accuracy: 0.973
6 - val_loss: 0.1951 - val_accuracy: 0.9461
Epoch 31/50
235/235 [=====] - 18s 77ms/step - loss: 0.0445 - accuracy: 0.984
8 - val_loss: 0.1676 - val_accuracy: 0.9650
Epoch 32/50
235/235 [=====] - 17s 73ms/step - loss: 0.0542 - accuracy: 0.982
2 - val_loss: 0.2234 - val_accuracy: 0.9368
Epoch 33/50
235/235 [=====] - 17s 74ms/step - loss: 0.0762 - accuracy: 0.973
9 - val_loss: 0.1967 - val_accuracy: 0.9587
Epoch 34/50
235/235 [=====] - 17s 73ms/step - loss: 0.0347 - accuracy: 0.988
3 - val_loss: 0.1550 - val_accuracy: 0.9646
Epoch 35/50
235/235 [=====] - 19s 80ms/step - loss: 0.0214 - accuracy: 0.993
0 - val_loss: 0.1940 - val_accuracy: 0.9615
Epoch 36/50
235/235 [=====] - 17s 73ms/step - loss: 0.0650 - accuracy: 0.977
9 - val_loss: 0.2945 - val_accuracy: 0.9330
Epoch 37/50
235/235 [=====] - 18s 75ms/step - loss: 0.0881 - accuracy: 0.971
6 - val_loss: 0.2232 - val_accuracy: 0.9582
Epoch 38/50
235/235 [=====] - 17s 73ms/step - loss: 0.0211 - accuracy: 0.993
6 - val_loss: 0.1789 - val_accuracy: 0.9609
Epoch 39/50
235/235 [=====] - 18s 75ms/step - loss: 0.0355 - accuracy: 0.988
1 - val_loss: 0.1644 - val_accuracy: 0.9676
Epoch 40/50
235/235 [=====] - 17s 73ms/step - loss: 0.0271 - accuracy: 0.990
7 - val_loss: 0.2005 - val_accuracy: 0.9622
Epoch 41/50
235/235 [=====] - 18s 74ms/step - loss: 0.0232 - accuracy: 0.992
5 - val_loss: 0.2582 - val_accuracy: 0.9523
Epoch 42/50
235/235 [=====] - 18s 75ms/step - loss: 0.1141 - accuracy: 0.964
7 - val_loss: 0.1601 - val_accuracy: 0.9615
Epoch 43/50
235/235 [=====] - 17s 73ms/step - loss: 0.0273 - accuracy: 0.990
8 - val_loss: 0.1969 - val_accuracy: 0.9628
Epoch 44/50

```

Epoch 44/50
235/235 [=====] - 18s 76ms/step - loss: 0.0158 - accuracy: 0.995
1 - val_loss: 0.1818 - val_accuracy: 0.9714
Epoch 45/50
235/235 [=====] - 17s 73ms/step - loss: 0.0133 - accuracy: 0.995
3 - val_loss: 0.1677 - val_accuracy: 0.9684
Epoch 46/50
235/235 [=====] - 18s 76ms/step - loss: 0.0994 - accuracy: 0.969
1 - val_loss: 0.1632 - val_accuracy: 0.9654
Epoch 47/50
235/235 [=====] - 17s 74ms/step - loss: 0.0232 - accuracy: 0.992
0 - val_loss: 0.1358 - val_accuracy: 0.9760
Epoch 48/50
235/235 [=====] - 18s 75ms/step - loss: 0.0120 - accuracy: 0.996
0 - val_loss: 0.1974 - val_accuracy: 0.9625
Epoch 49/50
235/235 [=====] - 18s 75ms/step - loss: 0.0500 - accuracy: 0.983
8 - val_loss: 0.2534 - val_accuracy: 0.9525
Epoch 50/50
235/235 [=====] - 18s 75ms/step - loss: 0.0667 - accuracy: 0.979
1 - val_loss: 0.1998 - val_accuracy: 0.9625

```

In [47]:

```
print(model_CNN.summary())
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
=====		
conv2d_4 (Conv2D)	(None, 28, 28, 16)	448
max_pooling2d_2 (MaxPooling2D)	(None, 14, 14, 16)	0
conv2d_5 (Conv2D)	(None, 14, 14, 32)	4640
max_pooling2d_3 (MaxPooling2D)	(None, 7, 7, 32)	0
conv2d_6 (Conv2D)	(None, 7, 7, 64)	18496
max_pooling2d_4 (MaxPooling2D)	(None, 4, 4, 64)	0
conv2d_7 (Conv2D)	(None, 4, 4, 128)	73856
max_pooling2d_5 (MaxPooling2D)	(None, 2, 2, 128)	0
flatten_1 (Flatten)	(None, 512)	0
dense_2 (Dense)	(None, 64)	32832
dense_3 (Dense)	(None, 32)	2080
dense_4 (Dense)	(None, 7)	231
=====		
Total params: 132,583		
Trainable params: 132,583		
Non-trainable params: 0		
None		

In [48]:

```

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))

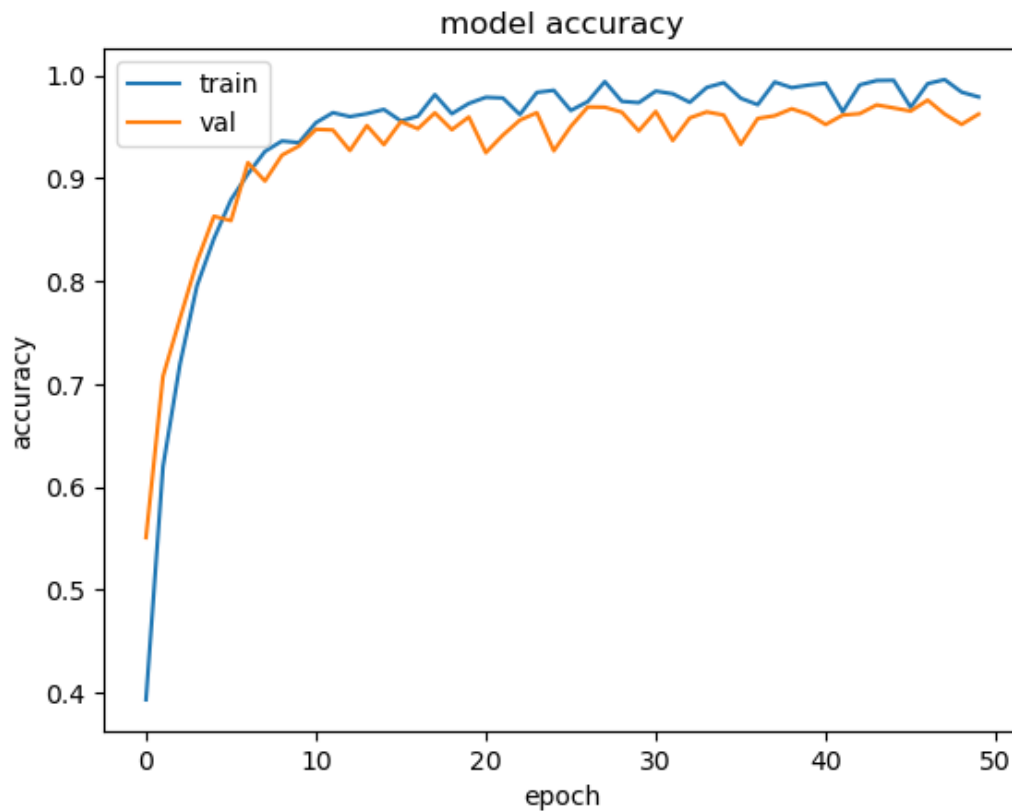
```

Test Loss: 0.10222

test loss: 0.1932
Test Accuracy: 96.48%

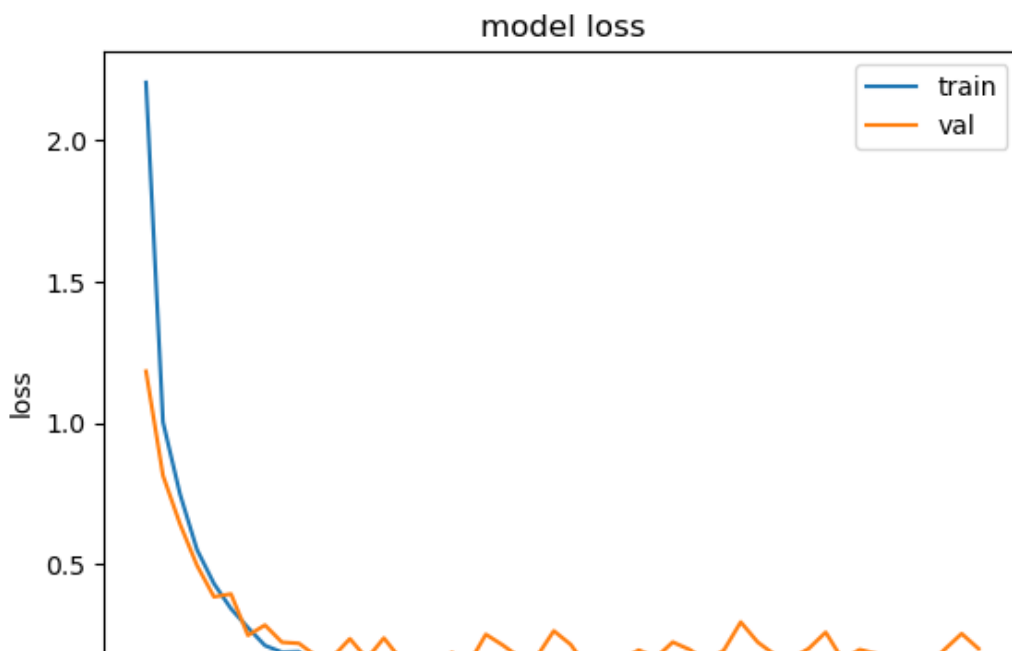
In [49]:

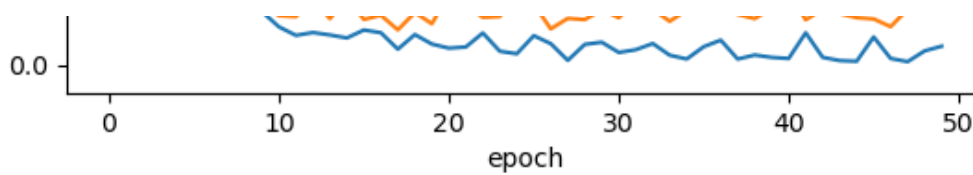
```
plt.plot(history.history['accuracy'])  
plt.plot(history.history['val_accuracy'])  
plt.title('model accuracy')  
plt.ylabel('accuracy')  
plt.xlabel('epoch')  
plt.legend(['train', 'val'], loc='upper left')  
plt.show()
```



In [50]:

```
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 [51]:

```
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[0:10])
```

294/294 [=====] - 3s 9ms/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]

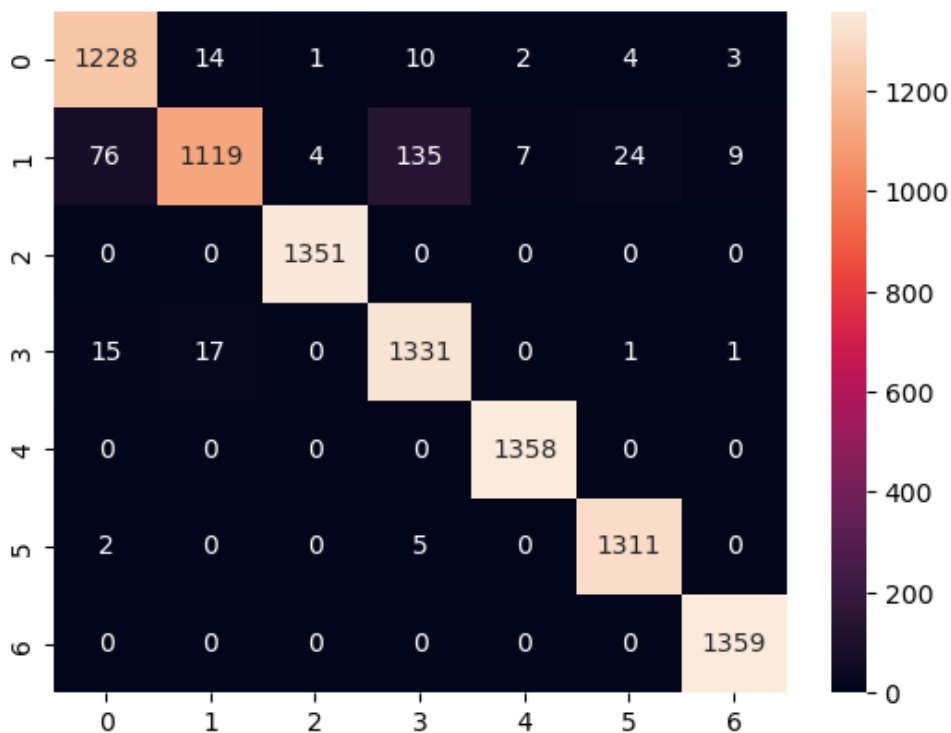
In [52]:

```
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='')
```

```
[[1228  14   1  10   2   4   3]
 [ 76 1119   4  135   7  24   9]
 [  0   0 1351   0   0   0   0]
 [ 15  17   0 1331   0   1   1]
 [  0   0   0   0 1358   0   0]
 [  2   0   0   5   0 1311   0]
 [  0   0   0   0   0   0 1359]]
```

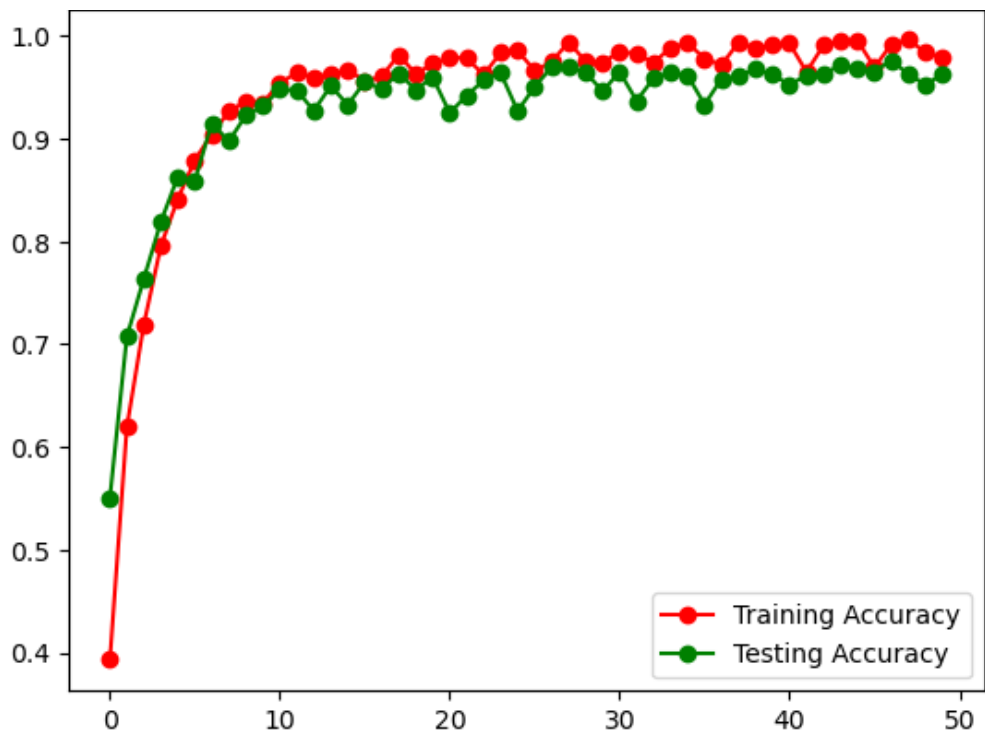
Out[52]:

<AxesSubplot:>



In [53]:

```
#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 [54]:

```
#predicting
y_pred_CNN = model.predict(X_test).round()
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 [=====] - 3s 9ms/step

9387 9387

score	support		precision	recall	f1-
('akiec', 'Actinic keratoses and intraepithelial carcinomae')	0.00 1359		0.99	1.00	1
		('bcc', ' basal cell carcinoma')	0.99	1.00	
0.99	1318				
		('bkl', 'benign keratosis-like lesions')	0.94	0.98	
0.96	1262				
		('df', 'dermatofibroma')	1.00	1.00	
1.00	1351				
		('nv', ' melanocytic nevi')	0.99	0.86	
0.92	1374				
		('vasc', ' pyogenic granulomas and hemorrhage')	1.00	1.00	
1.00	1358				
		('mel', 'melanoma')	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				

NEW CNN Model 4-Layers with Early Stopping & Reduce Learning Rate

In [65]:

```
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, mode='auto')
history_1 = 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 [=====] - 20s 43ms/step - loss: 5.8255e-04 - accuracy: 1.0000 - val_loss: 0.1584 - val_accuracy: 0.9743 - lr: 1.0000e-07
Epoch 2/50
470/470 [=====] - 19s 41ms/step - loss: 5.8166e-04 - accuracy: 1.0000 - val_loss: 0.1584 - val_accuracy: 0.9743 - lr: 1.0000e-07
Epoch 3/50
470/470 [=====] - 19s 41ms/step - loss: 5.8055e-04 - accuracy: 1.0000 - val_loss: 0.1584 - val_accuracy: 0.9743 - lr: 1.0000e-07
Epoch 4/50
470/470 [=====] - ETA: 0s - loss: 5.7919e-04 - accuracy: 1.0000
Epoch 4: ReduceLRonPlateau reducing learning rate to 1.000000082740371e-08.
470/470 [=====] - 19s 41ms/step - loss: 5.7919e-04 - accuracy: 1.0000 - val_loss: 0.1585 - val_accuracy: 0.9743 - lr: 1.0000e-07
Epoch 5/50
470/470 [=====] - 20s 42ms/step - loss: 5.7791e-04 - accuracy: 1.0000 - val_loss: 0.1585 - val_accuracy: 0.9743 - lr: 1.0000e-08
Epoch 6/50
470/470 [=====] - 20s 43ms/step - loss: 5.7783e-04 - accuracy: 1.0000 - val_loss: 0.1585 - val_accuracy: 0.9743 - lr: 1.0000e-08
Epoch 7/50
469/470 [=====>.] - ETA: 0s - loss: 5.7776e-04 - accuracy: 1.0000
Epoch 7: ReduceLRonPlateau reducing learning rate to 1.000000082740371e-09.
470/470 [=====] - 20s 42ms/step - loss: 5.7773e-04 - accuracy: 1.0000 - val_loss: 0.1585 - val_accuracy: 0.9743 - lr: 1.0000e-08
Epoch 8/50
470/470 [=====] - 20s 42ms/step - loss: 5.7763e-04 - accuracy: 1.0000 - val_loss: 0.1585 - val_accuracy: 0.9743 - lr: 1.0000e-09
Epoch 9/50
470/470 [=====] - 20s 42ms/step - loss: 5.7763e-04 - accuracy: 1.0000 - val_loss: 0.1585 - val_accuracy: 0.9743 - lr: 1.0000e-09
Epoch 10/50
469/470 [=====>.] - ETA: 0s - loss: 5.7674e-04 - accuracy: 1.0000
Epoch 10: ReduceLRonPlateau reducing learning rate to 1.000000082740371e-10.
470/470 [=====] - 20s 42ms/step - loss: 5.7763e-04 - accuracy: 1.0000 - val_loss: 0.1585 - val_accuracy: 0.9743 - lr: 1.0000e-09
Epoch 11/50
470/470 [=====] - 20s 42ms/step - loss: 5.7763e-04 - accuracy: 1.0000 - val_loss: 0.1585 - val_accuracy: 0.9743 - lr: 1.0000e-10
Epoch 11: early stopping

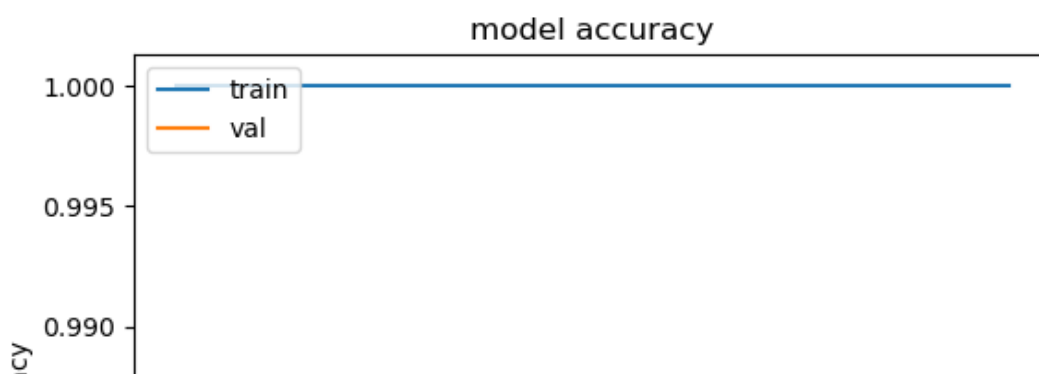
```

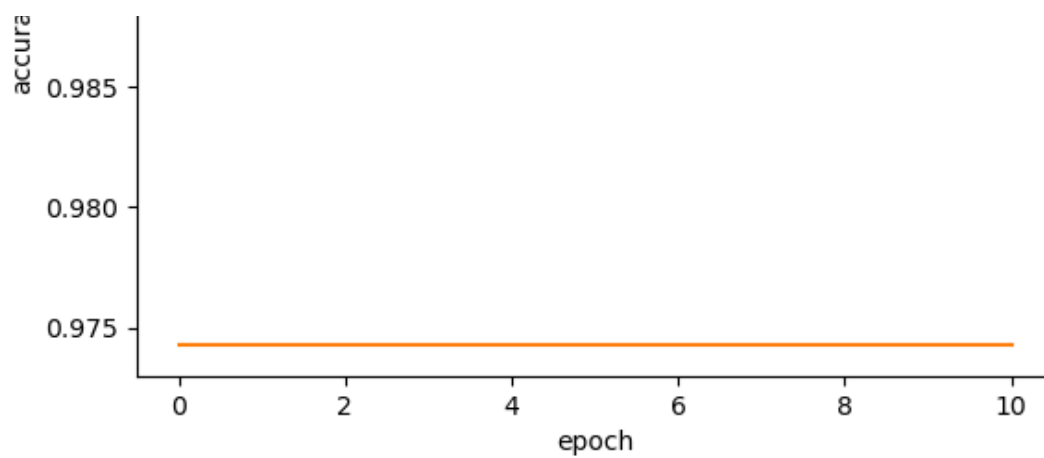
In [66]:

```

plt.plot(history_1.history['accuracy'])
plt.plot(history_1.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'val'], loc='upper left')
plt.show()

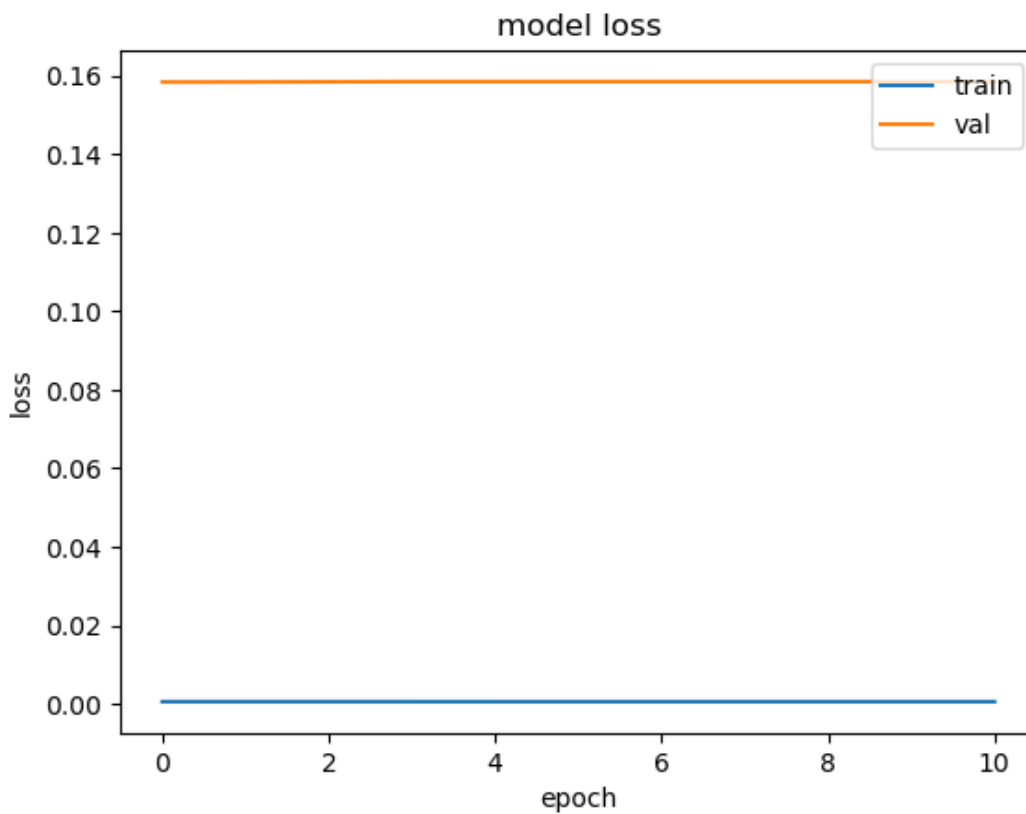
```





In [67]:

```
plt.plot(history_1.history['loss'])
plt.plot(history_1.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'val'], loc='upper right')
plt.show()
```



In [68]:

```
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 [=====] - 3s 9ms/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 [69]:

```
results_1 = 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: 0.19332
Test Accuracy: 96.48%

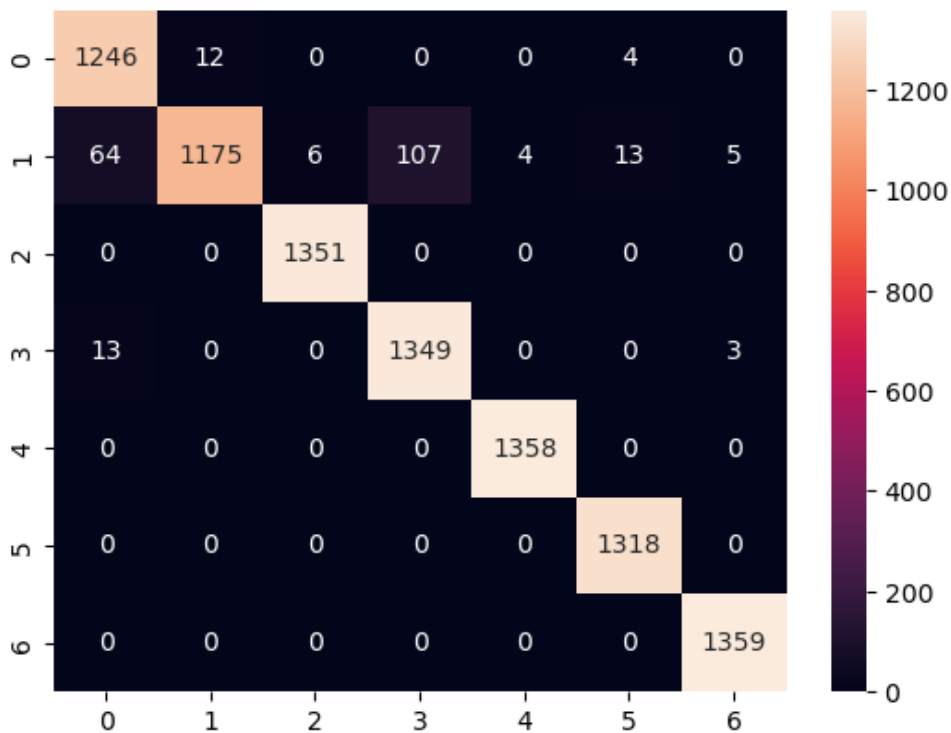
In [60]:

```
cm_CNN_lr = 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_lr, annot = True, fmt='')
```

```
[[1246  12  0  0  0  4  0]
 [ 64 1175  6 107  4 13  5]
 [  0  0 1351  0  0  0  0]
 [ 13  0  0 1349  0  0  3]
 [  0  0  0  0 1358  0  0]
 [  0  0  0  0  0 1318  0]
 [  0  0  0  0  0  0 1359]]
```

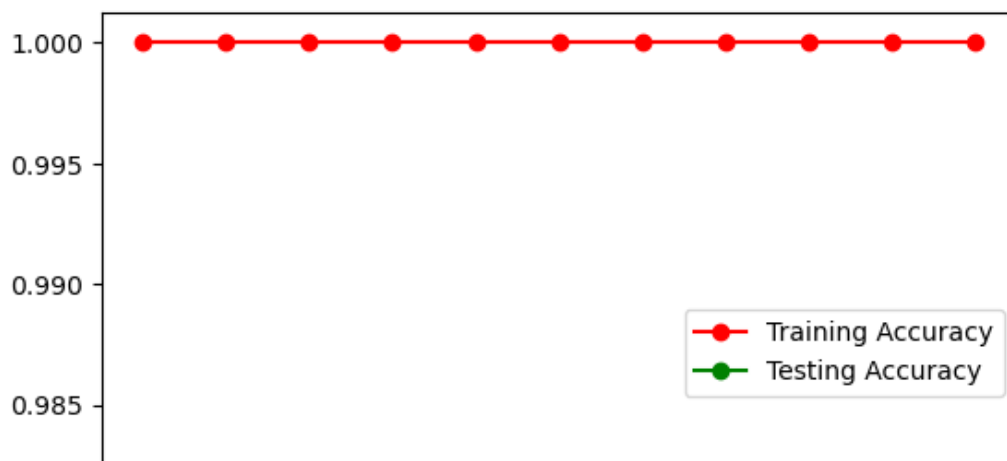
Out[60]:

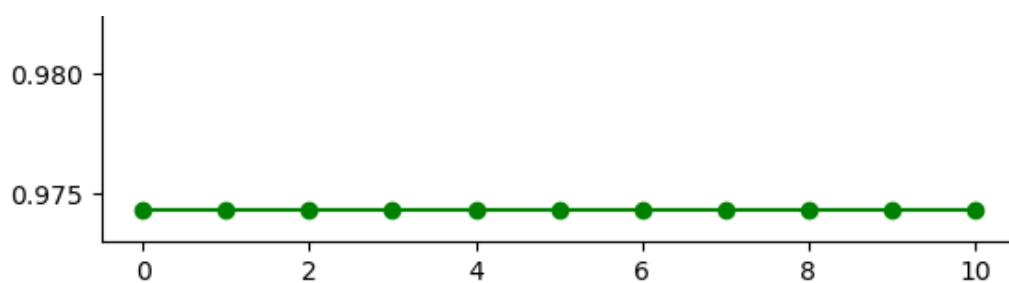
<AxesSubplot:>



In [70]:

```
#training acc vs testing acc graph
plt.plot(history_1.history["accuracy"] , 'ro-' , label = "Training Accuracy")
plt.plot(history_1.history["val_accuracy"] , 'go-' , label = "Testing Accuracy")
plt.legend()
plt.show()
```





In [71]:

```
y_pred_L = model_CNN.predict(X_test).round()
```

294/294 [=====] - 3s 9ms/step

In [72]:

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

294/294 [=====] - 3s 10ms/step

score	support		precision	recall	f1-
0.00	1359	('akiec', 'Actinic keratoses and intraepithelial carcinomae')	0.99	1.00	1
0.99	1318	('bcc', ' basal cell carcinoma')	0.99	1.00	
0.96	1262	('bkl', 'benign keratosis-like lesions')	0.94	0.98	
1.00	1351	('df', 'dermatofibroma')	1.00	1.00	
0.92	1374	('nv', ' melanocytic nevi')	0.99	0.86	
1.00	1358	('vasc', ' pyogenic granulomas and hemorrhage')	1.00	1.00	
0.96	1365	('mel', 'melanoma')	0.93	0.99	
accuracy					
0.98	9387				
macro avg					
0.98	9387		0.98	0.98	
weighted avg					
0.98	9387		0.98	0.98	

In [73]:

```
# 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 0x7f3761f80b50>
1 <keras.layers.pooling.max_pooling2d.MaxPooling2D object at 0x7f37620e40d0>
2 <keras.layers.convolutional.conv2d.Conv2D object at 0x7f3761f33150>
3 <keras.layers.pooling.max_pooling2d.MaxPooling2D object at 0x7f376df1d190>
4 <keras.layers.convolutional.conv2d.Conv2D object at 0x7f3761fbd690>
5 <keras.layers.pooling.max_pooling2d.MaxPooling2D object at 0x7f376088d510>
6 <keras.layers.convolutional.conv2d.Conv2D object at 0x7f376db8b710>
7 <keras.layers.pooling.max_pooling2d.MaxPooling2D object at 0x7f37620b4290>
8 <keras.layers.resizing.flatten.Flatten object at 0x7f37608c3410>
9 <keras.layers.core.dense.Dense object at 0x7f37608c3f90>
10 <keras.layers.core.dense.Dense object at 0x7f376db8bc10>
11 <keras.lavers.core.dense.Dense object at 0x7f3760888090>
```

