In [ ]:
```
!pip install tensorflow scikit-learn
!pip install keras
!pip install tensorflow
```

In [1]:
```
import os
import numpy as np
import pandas as pd
import tensorflow as tf
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns
import random

from tensorflow.keras.preprocessing.image import ImageDataGenerator
```

In [2]:
```
# Load the CSV dataset
dataset_path = 'Dataset.csv'
df = pd.read_csv(dataset_path)
df.head()
```

Out[2]:

	pix-1	pix-2	pix-3	pix-4	pix-5	pix-6	pix-7	pix-8	pix-9	pix-10	...	pix-9992	pix-9993	pix-9994	pix-9995	pix-9996
0	183	185	193	220	220	226	222	221	158	122	...	112	112	112	113	121
1	20	14	9	8	9	10	9	8	6	5	...	230	230	230	230	230
2	7	8	10	12	14	17	17	16	13	8	...	229	229	229	229	229
3	26	22	17	14	12	11	11	11	10	9	...	232	232	232	232	232
4	63	52	25	15	14	5	8	5	9	8	...	90	101	106	110	112

5 rows × 10001 columns

In [3]:
```
df = df.sample(frac=1).reset_index(drop=True)
df.head()
```

Out[3]:

	pix-1	pix-2	pix-3	pix-4	pix-5	pix-6	pix-7	pix-8	pix-9	pix-10	...	pix-9992	pix-9993	pix-9994	pix-9995	pix-9996
0	14	11	8	8	11	17	21	24	16	4	...	233	232	232	232	232
1	177	189	201	205	214	239	247	255	254	255	...	231	238	162	110	186
2	142	139	142	112	49	35	31	18	14	13	...	152	155	154	155	155
3	224	244	255	255	255	254	252	255	255	251	...	41	39	43	105	234
4	174	179	177	173	178	174	177	176	171	131	...	179	178	178	177	177

5 rows × 10001 columns

In [4]:
```
# Split features and labels
X = df.drop('class', axis=1).values
```

```python
y = df['class'].values
```

In [5]:
```python
print(X)
```

```
[[ 14  11   8 ... 232 232 232]
 [177 189 201 ... 215 197 189]
 [142 139 142 ... 155 155 155]
 ...
 [177 175 175 ... 122 124 117]
 [225 222 217 ... 215 222 216]
 [ 14  10   8 ... 232 232 232]]
```

In [6]:
```python
print(y)
```

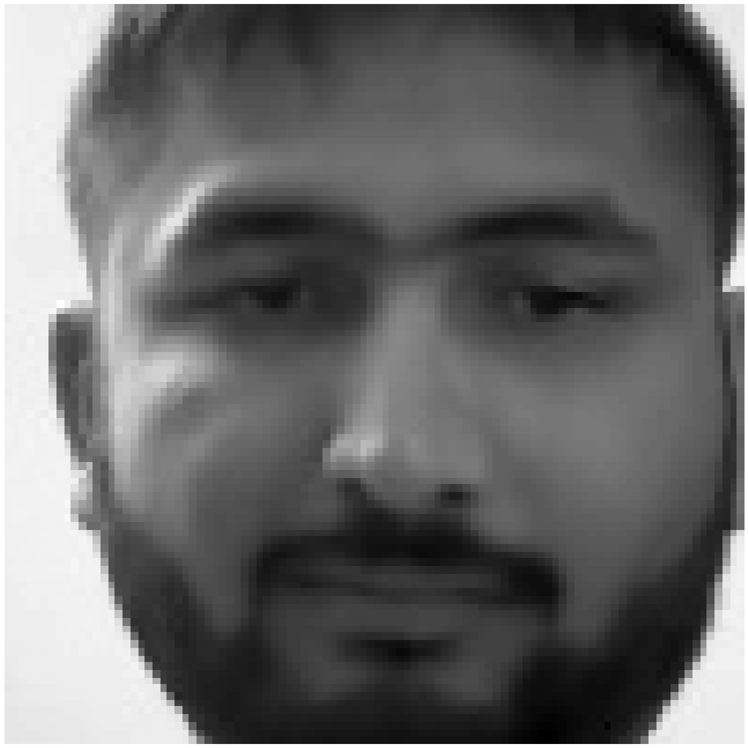
```
[1 4 5 ... 4 4 1]
```

In [7]:
```python
# Encode labels
label_encoder = LabelEncoder()
y = label_encoder.fit_transform(y)
```

In [8]:
```python
# Split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, randon
```

In [9]:
```python
# Reshape and normalize the features
X_train = X_train.reshape(-1, 100, 100, 1) / 255.0
X_test = X_test.reshape(-1, 100, 100, 1) / 255.0
```

In [22]:
```python
# Choose a random index
random_index = random.randint(0, len(X) - 1)

# Display the corresponding image
plt.imshow(X[random_index].reshape(100, 100), cmap='gray')
plt.title(f'Label: {y[random_index]}')
plt.axis('off')
plt.show()
```



In [23]:
```
# Define a Sequential model, which allows for linear stack of layers
model = tf.keras.models.Sequential([
    # Input layer with shape (100, 100, 1)
    tf.keras.layers.Input(shape=(100, 100, 1)),

    # Convolutional layer with 32 filters of size (3, 3) and ReLU activation fu
    tf.keras.layers.Conv2D(32, (3, 3), activation='relu'),

    # Max pooling layer with pool size (2, 2) and stride (2, 2)
    tf.keras.layers.MaxPooling2D(2, 2),

    # Convolutional layer with 64 filters of size (3, 3) and ReLU activation fu
    tf.keras.layers.Conv2D(64, (3, 3), activation='relu'),

    # Max pooling layer with pool size (2, 2) and stride (2, 2)
    tf.keras.layers.MaxPooling2D(2, 2),

    # Flatten layer to flatten the input
    tf.keras.layers.Flatten(),

    # Dense (fully connected) layer with 128 units and ReLU activation functio
    tf.keras.layers.Dense(128, activation='relu'),

    # Dropout layer with dropout rate of 0.5 to prevent overfitting
    tf.keras.layers.Dropout(0.5),

    # Output layer with 6 units and softmax activation function for classifica
    tf.keras.layers.Dense(6, activation='softmax')
])

# Compile the model with Adam optimizer, sparse categorical crossentropy loss,
model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metric
```

In [24]:
```
# Print the summary of the model
model.summary()
```

Model: "sequential_2"

Layer (type)	Output Shape	Param #
conv2d_4 (Conv2D)	(None, 98, 98, 32)	320
max_pooling2d_4 (MaxPooling2D)	(None, 49, 49, 32)	0
conv2d_5 (Conv2D)	(None, 47, 47, 64)	18,496
max_pooling2d_5 (MaxPooling2D)	(None, 23, 23, 64)	0
flatten_2 (Flatten)	(None, 33856)	0
dense_4 (Dense)	(None, 128)	4,333,696
dropout_2 (Dropout)	(None, 128)	0
dense_5 (Dense)	(None, 6)	774

Total params: 4,353,286 (16.61 MB)

Trainable params: 4,353,286 (16.61 MB)

Non-trainable params: 0 (0.00 B)

In [25]:
```
# Define the data augmentation parameters
datagen = ImageDataGenerator(
    rotation_range=20,      # Rotate the image by a random angle within the ran
    width_shift_range=0.1,  # Shift the image horizontally by a maximum of 10%
    height_shift_range=0.1, # Shift the image vertically by a maximum of 10% o
    shear_range=0.2,        # Apply shear transformation with a maximum shear a
    zoom_range=0.2,         # Zoom into the image by a maximum factor of 1.2
    horizontal_flip=True,   # Flip the image horizontally with a probability o
    fill_mode='nearest'     # Fill in newly created pixels after rotation or sh
)

# Create augmented training data generator
augmented_datagen = datagen.flow(X_train, y_train)

# Train the model on the training data (X_train and y_train) for 20 epochs,
# while validating its performance on the test data (X_test and y_test)
history = model.fit(datagen.flow(X_train, y_train), epochs=20, validation_data=
```

```
Epoch 1/20
 1/43 ━━━━━━━━━━━━━━━━━━━━ 19s 472ms/step - accuracy: 0.1562 - loss: 1.8041
```

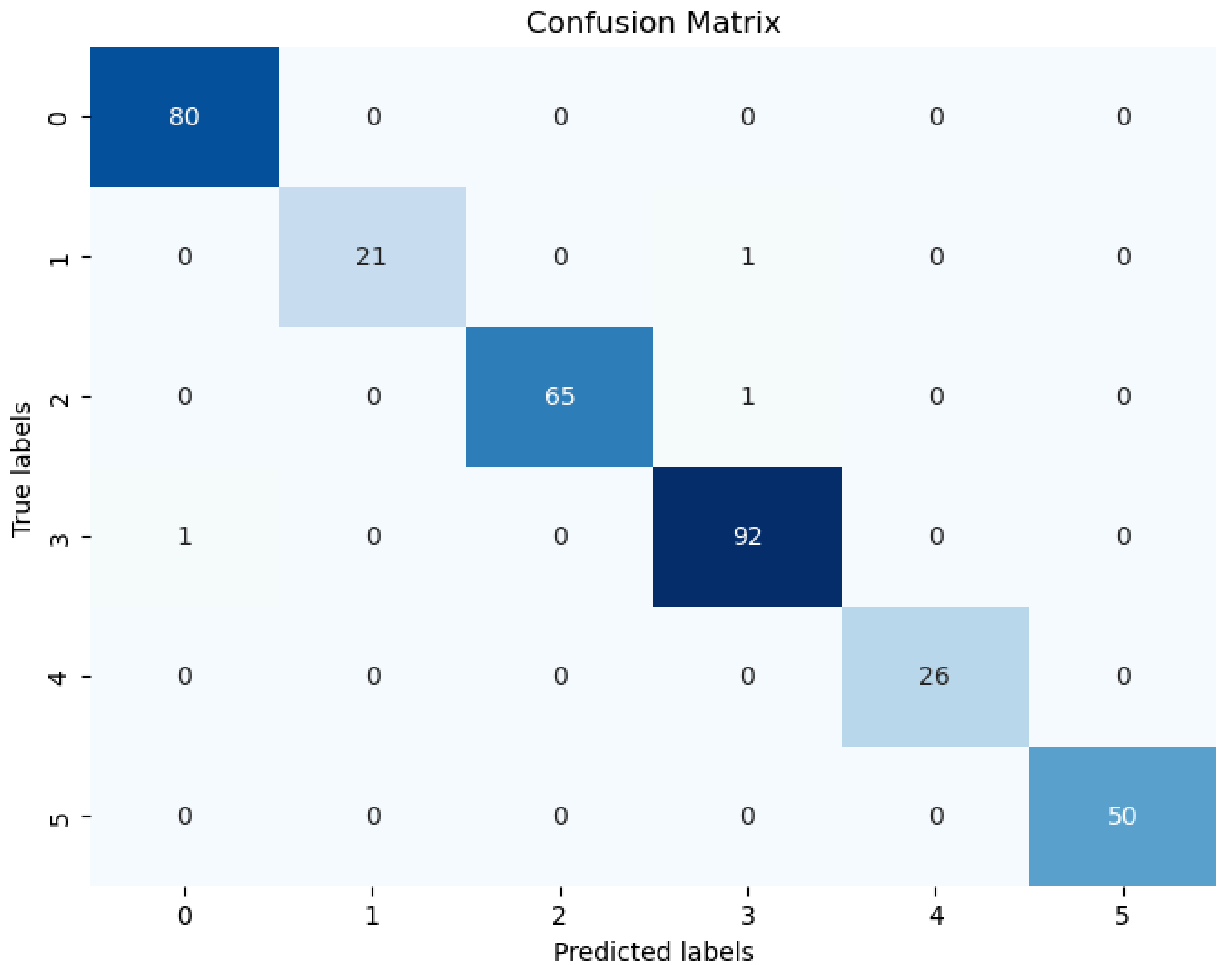
```
/Users/harshitgupta/anaconda3/lib/python3.11/site-packages/keras/src/trainers/
data_adapters/py_dataset_adapter.py:121: UserWarning: Your `PyDataset` class s
hould call `super().__init__(**kwargs)` in its constructor. `**kwargs` can inc
lude `workers`, `use_multiprocessing`, `max_queue_size`. Do not pass these arg
uments to `fit()`, as they will be ignored.
  self._warn_if_super_not_called()
```

```
43/43 ━━━━━━━━━━━━━━━━━━━━ 3s 70ms/step - accuracy: 0.4369 - loss: 1.4890 - va
l_accuracy: 0.8754 - val_loss: 0.4668
Epoch 2/20
43/43 ━━━━━━━━━━━━━━━━━━━━ 3s 68ms/step - accuracy: 0.8470 - loss: 0.5040 - va
l_accuracy: 0.9496 - val_loss: 0.2412
Epoch 3/20
43/43 ━━━━━━━━━━━━━━━━━━━━ 3s 68ms/step - accuracy: 0.8906 - loss: 0.3717 - va
l_accuracy: 0.9496 - val_loss: 0.2109
Epoch 4/20
43/43 ━━━━━━━━━━━━━━━━━━━━ 3s 72ms/step - accuracy: 0.9204 - loss: 0.2927 - va
l_accuracy: 0.9555 - val_loss: 0.1326
Epoch 5/20
43/43 ━━━━━━━━━━━━━━━━━━━━ 3s 69ms/step - accuracy: 0.9349 - loss: 0.2292 - va
l_accuracy: 0.9555 - val_loss: 0.0951
Epoch 6/20
43/43 ━━━━━━━━━━━━━━━━━━━━ 3s 68ms/step - accuracy: 0.9475 - loss: 0.1626 - va
l_accuracy: 0.9792 - val_loss: 0.0972
Epoch 7/20
43/43 ━━━━━━━━━━━━━━━━━━━━ 3s 72ms/step - accuracy: 0.9233 - loss: 0.2056 - va
l_accuracy: 0.9674 - val_loss: 0.1091
Epoch 8/20
43/43 ━━━━━━━━━━━━━━━━━━━━ 3s 68ms/step - accuracy: 0.9594 - loss: 0.1287 - va
l_accuracy: 0.9763 - val_loss: 0.0889
Epoch 9/20
43/43 ━━━━━━━━━━━━━━━━━━━━ 3s 68ms/step - accuracy: 0.9623 - loss: 0.1538 - va
l_accuracy: 0.9881 - val_loss: 0.0631
Epoch 10/20
43/43 ━━━━━━━━━━━━━━━━━━━━ 3s 68ms/step - accuracy: 0.9675 - loss: 0.1103 - va
l_accuracy: 0.9911 - val_loss: 0.0671
Epoch 11/20
43/43 ━━━━━━━━━━━━━━━━━━━━ 3s 70ms/step - accuracy: 0.9672 - loss: 0.1143 - va
l_accuracy: 0.9822 - val_loss: 0.0952
Epoch 12/20
43/43 ━━━━━━━━━━━━━━━━━━━━ 3s 71ms/step - accuracy: 0.9505 - loss: 0.1292 - va
l_accuracy: 0.9674 - val_loss: 0.0931
Epoch 13/20
43/43 ━━━━━━━━━━━━━━━━━━━━ 3s 70ms/step - accuracy: 0.9577 - loss: 0.1256 - va
l_accuracy: 0.9941 - val_loss: 0.0436
Epoch 14/20
43/43 ━━━━━━━━━━━━━━━━━━━━ 3s 73ms/step - accuracy: 0.9443 - loss: 0.1782 - va
l_accuracy: 0.9881 - val_loss: 0.0524
Epoch 15/20
43/43 ━━━━━━━━━━━━━━━━━━━━ 3s 73ms/step - accuracy: 0.9693 - loss: 0.0853 - va
l_accuracy: 0.9970 - val_loss: 0.0419
Epoch 16/20
43/43 ━━━━━━━━━━━━━━━━━━━━ 3s 69ms/step - accuracy: 0.9713 - loss: 0.0846 - va
l_accuracy: 0.9644 - val_loss: 0.0909
Epoch 17/20
43/43 ━━━━━━━━━━━━━━━━━━━━ 3s 70ms/step - accuracy: 0.9519 - loss: 0.1511 - va
l_accuracy: 0.9911 - val_loss: 0.0446
Epoch 18/20
43/43 ━━━━━━━━━━━━━━━━━━━━ 3s 68ms/step - accuracy: 0.9661 - loss: 0.1018 - va
l_accuracy: 0.9911 - val_loss: 0.0445
Epoch 19/20
43/43 ━━━━━━━━━━━━━━━━━━━━ 3s 72ms/step - accuracy: 0.9729 - loss: 0.0704 - va
l_accuracy: 0.9911 - val_loss: 0.0464
Epoch 20/20
43/43 ━━━━━━━━━━━━━━━━━━━━ 3s 71ms/step - accuracy: 0.9755 - loss: 0.0626 - va
l_accuracy: 0.9911 - val_loss: 0.0399
```

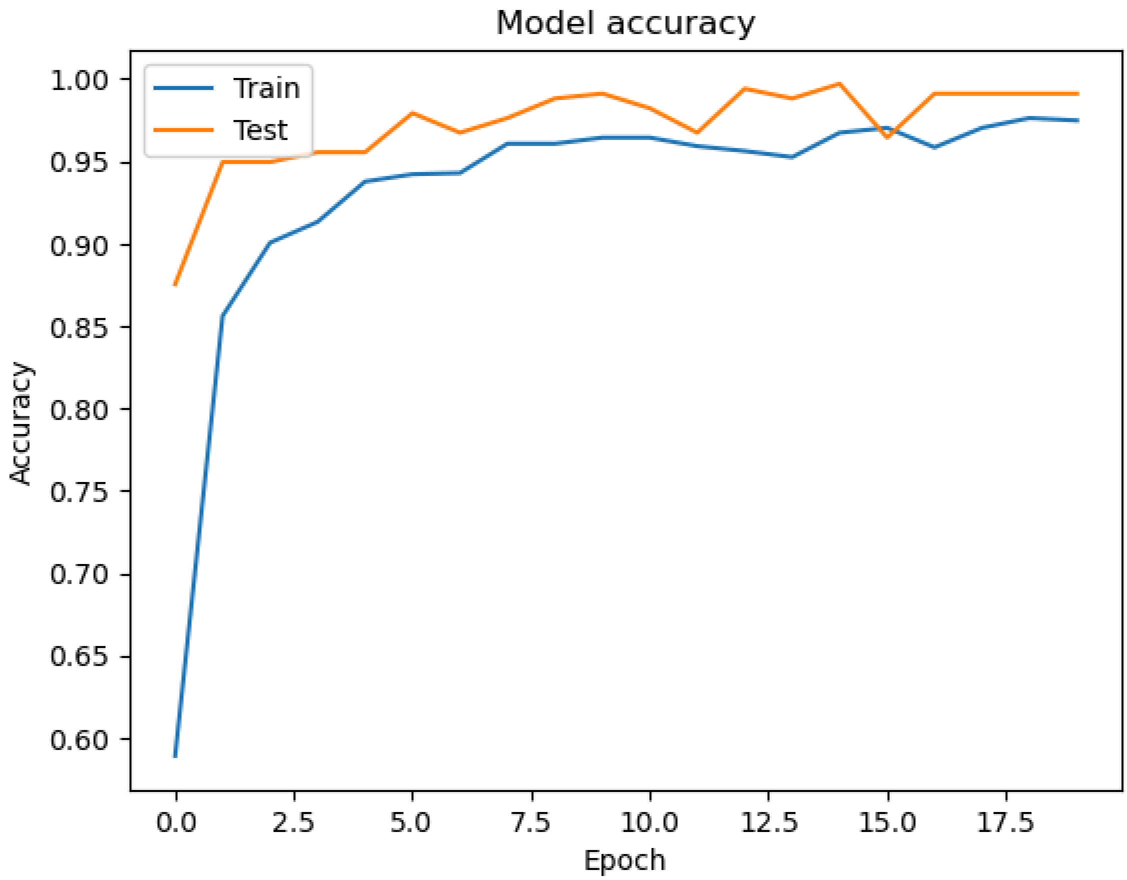
In [26]:
```
# Evaluate the model on the test set
test_loss, test_acc = model.evaluate(X_test, y_test)
print(f'Test Accuracy: {test_acc}')

# Make predictions
y_pred = np.argmax(model.predict(X_test), axis=-1)

# Print classification report
print(classification_report(y_test, y_pred))
```

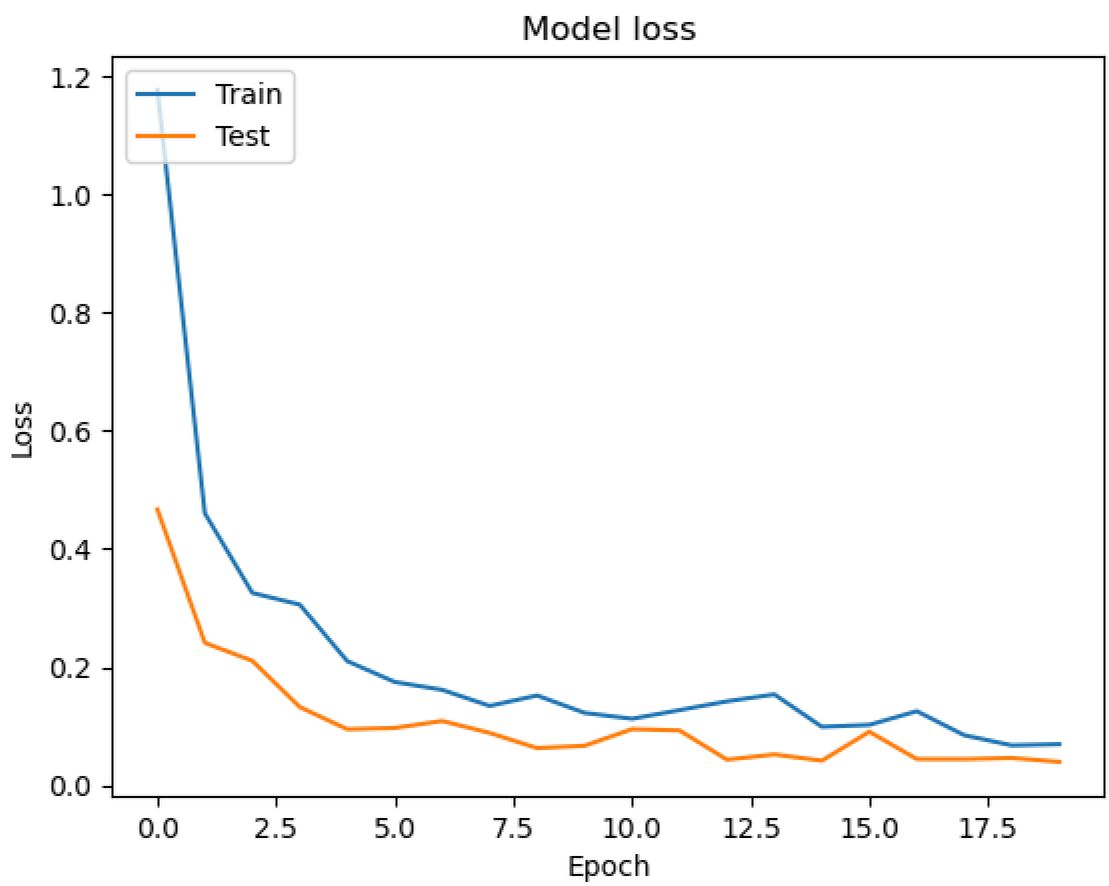
```
11/11 ━━━━━━━━━━━━━━━━━━━━ 0s 16ms/step - accuracy: 0.9922 - loss: 0.0230
Test Accuracy: 0.9910979270935059
11/11 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step
              precision    recall  f1-score   support

           0       0.99      1.00      0.99        80
           1       1.00      0.95      0.98        22
           2       1.00      0.98      0.99        66
           3       0.98      0.99      0.98        93
           4       1.00      1.00      1.00        26
           5       1.00      1.00      1.00        50

    accuracy                           0.99       337
   macro avg       0.99      0.99      0.99       337
weighted avg       0.99      0.99      0.99       337
```

In [27]:
```
# Calculate the confusion matrix using the true labels (y_test) and predicted
conf_matrix = confusion_matrix(y_test, y_pred)

# Plot the confusion matrix as a heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', cbar=False)
plt.xlabel('Predicted labels')  # Label for the x-axis representing predicted
plt.ylabel('True labels')  # Label for the y-axis representing true labels
plt.title('Confusion Matrix')  # Title of the plot
plt.show()  # Display the plot
```



In [28]:
```
# Plot training & test accuracy values over epochs
plt.plot(history.history['accuracy'])  # Plot training accuracy
plt.plot(history.history['val_accuracy'])  # Plot validation accuracy
plt.title('Model accuracy')  # Title of the plot
plt.ylabel('Accuracy')  # Label for the y-axis representing accuracy
plt.xlabel('Epoch')  # Label for the x-axis representing epochs
plt.legend(['Train', 'Test'], loc='upper left')  # Add legend for train and tes
plt.show()  # Display the plot

# Plot training & test loss values over epochs
plt.plot(history.history['loss'])  # Plot training loss
plt.plot(history.history['val_loss'])  # Plot validation loss
plt.title('Model loss')  # Title of the plot
plt.ylabel('Loss')  # Label for the y-axis representing loss
plt.xlabel('Epoch')  # Label for the x-axis representing epochs
plt.legend(['Train', 'Test'], loc='upper left')  # Add legend for train and tes
plt.show()  # Display the plot
```

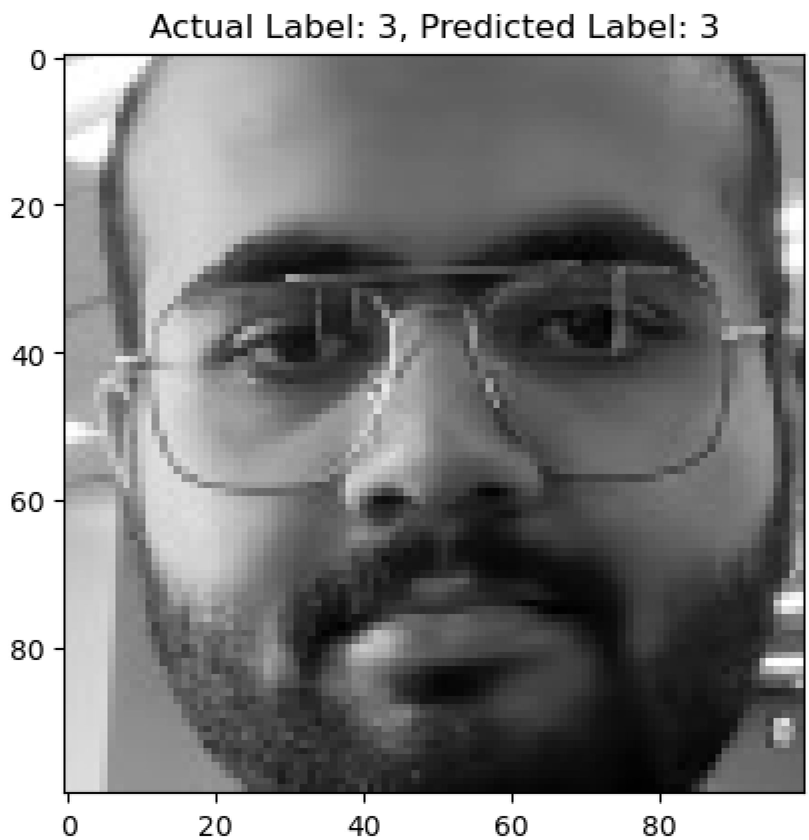




In [30]:
```
# Choose a random index from the test set
random_index = random.randint(0, len(X_test) - 1)
```

```
# Get the corresponding image, actual label, and predicted label
random_image = X_test[random_index]  # Select the image corresponding to the ra
actual_label = y_test[random_index]  # Get the actual label of the selected ima
predicted_label = np.argmax(model.predict(random_image.reshape(1, 100, 100, 1)

# Display the image along with its actual and predicted labels
plt.imshow(random_image.reshape(100, 100), cmap='gray')  # Plot the image
plt.title(f'Actual Label: {actual_label}, Predicted Label: {predicted_label[0]
plt.axis('on')  # Turn on axis
plt.show()  # Display the plot
```

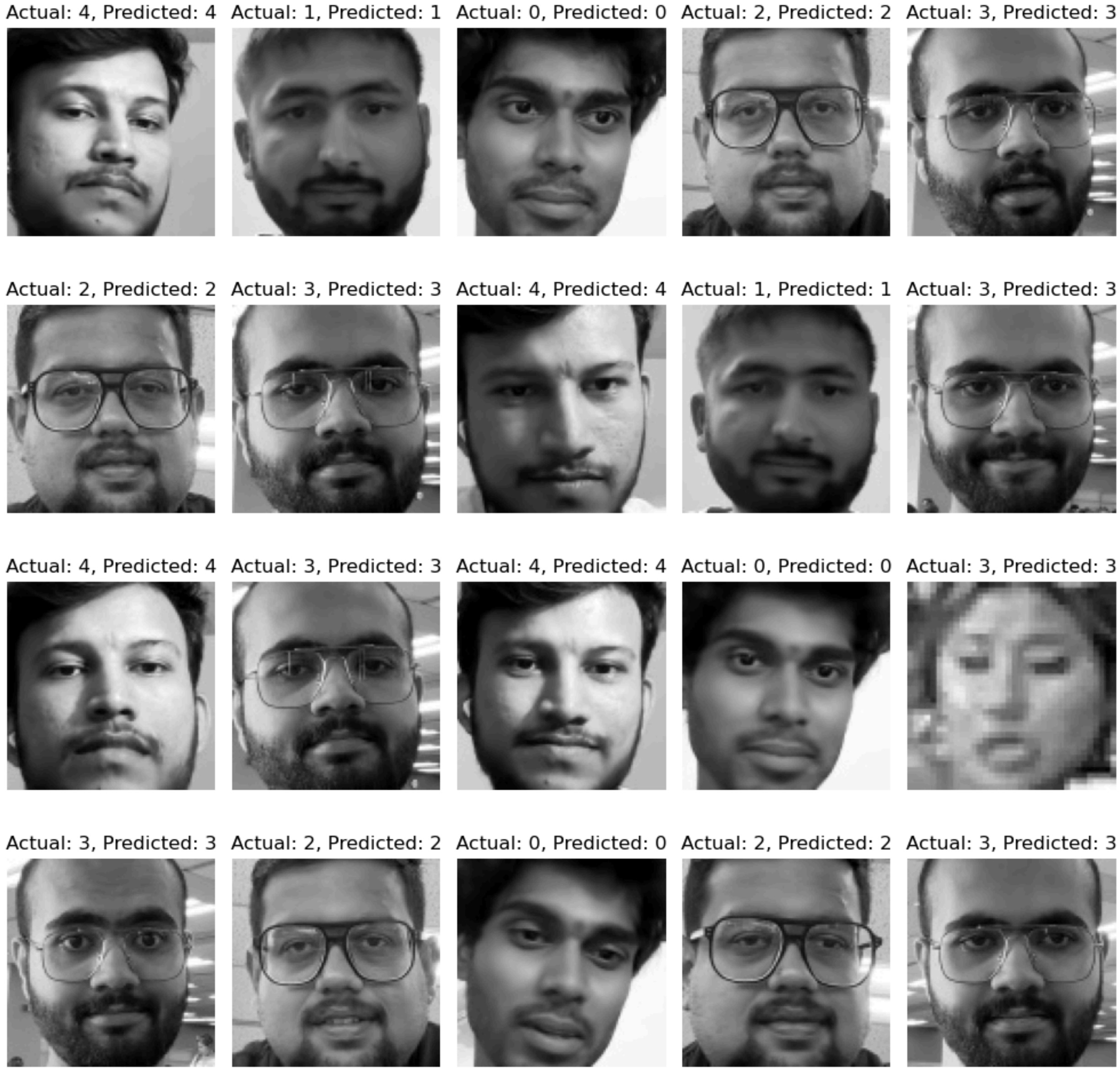
```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 14ms/step
```



In [31]:
```
def plot_images_with_predictions(model, X_test, y_test, num_images=20, grid_si
    # Generate random indices for selecting images
    random_indices = random.sample(range(len(X_test)), num_images)

    # Create subplots
    fig, axes = plt.subplots(*grid_size, figsize=(10, 10))

    # Flatten axes if grid_size is 1x1
    if grid_size == (1, 1):
        axes = np.array([axes])

    # Loop through the random indices and plot images with predictions
    for i, idx in enumerate(random_indices):
        # Get image, actual label, and predicted label
        image = X_test[idx]
        actual_label = y_test[idx]
        predicted_label = np.argmax(model.predict(image.reshape(1, 100, 100, 1

        # Plot the image
        row = i // grid_size[1]
```

```
        col = i % grid_size[1]
        axes[row, col].imshow(image.reshape(100, 100), cmap='gray')
        axes[row, col].set_title(f'Actual: {actual_label}, Predicted: {predicte
        axes[row, col].axis('off')

    # Adjust layout and show plot
    plt.tight_layout()
    plt.show()

# Usage example
plot_images_with_predictions(model, X_test, y_test)
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step
```


Actual: 4, Predicted: 4
Actual: 1, Predicted: 1
Actual: 0, Predicted: 0
Actual: 2, Predicted: 2
Actual: 3, Predicted: 3
Actual: 2, Predicted: 2
Actual: 3, Predicted: 3
Actual: 4, Predicted: 4
Actual: 1, Predicted: 1
Actual: 3, Predicted: 3
Actual: 4, Predicted: 4
Actual: 3, Predicted: 3
Actual: 4, Predicted: 4
Actual: 0, Predicted: 0
Actual: 3, Predicted: 3
Actual: 3, Predicted: 3
Actual: 2, Predicted: 2
Actual: 0, Predicted: 0
Actual: 2, Predicted: 2
Actual: 3, Predicted: 3

In [ ]: