Image Classification (Cat/Dog)

The aim of this project is to build and evaluate a robust binary image classification model that can accurately distinguish between cats and dogs using a Convolutional Neural Network (CNN)

In [1]:
```
# import the required libraries
import random
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# ignore harmless warnings
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

In [3]:
```
# Importing the data
# Importing the training data
x_train = np.loadtxt('/content/drive/MyDrive/Colab Notebooks/Datasets/Cat and
y_train = np.loadtxt('/content/drive/MyDrive/Colab Notebooks/Datasets/Cat and

# Importing the testing data
x_test = np.loadtxt('/content/drive/MyDrive/Colab Notebooks/Datasets/Cat and D
y_test = np.loadtxt('/content/drive/MyDrive/Colab Notebooks/Datasets/Cat and D
```

In [4]:
```
x_train
```

Out[4]:
```
array([[ 37.,  39.,  25., ...,  58.,  54.,  29.],
       [131., 128., 135., ...,  71.,  96.,  74.],
       [ 80.,  92.,  88., ..., 124., 119.,  99.],
       ...,
       [231., 226., 230., ...,  62.,  65.,  72.],
       [ 61.,  61.,  63., ..., 135., 123., 123.],
       [ 64.,  31.,  12., ...,  61.,  49.,  35.]])
```

In [5]:
```
y_train # 0 - Dog and 1 - Cat
```

Out[5]:
```
array([0., 0., 0., ..., 1., 1., 1.])
```

In [6]:
```
x_test
```

```
Out[6]: array([[118.,  82.,  96., ..., 140.,  79.,  16.],
               [223., 211., 163., ...,  70.,  73.,  78.],
               [ 73.,  67.,  43., ..., 222., 211., 165.],
               ...,
               [249., 245., 242., ...,  73.,  72.,  68.],
               [ 97.,  96., 102., ...,  84.,  78.,  80.],
               [ 94.,  66.,  63., ..., 119.,  96.,  80.]])
```

```
In [7]: # Dimension of the data
        print(x_train.shape)
        print(y_train.shape)
        print(x_test.shape)
        print(y_test.shape)

        # (2000, 30000) --> 2000 images of each having 30000 columns, each column is a
```

```
(2000, 30000)
(2000,)
(400, 30000)
(400,)
```

```
In [8]: # pixel values
        print('Minimum pixel value:', x_train.min())
        print('Maximum pixel value:', x_train.max())

        # This represents the image can be RGB
```

```
Minimum pixel value: 0.0
Maximum pixel value: 255.0
```

```
In [9]: # reshape the training data
        x_train = x_train.reshape(len(x_train), 100, 100, 3)
        y_train = y_train.reshape(len(y_train), 1)

        # reshape the test data
        x_test = x_test.reshape(len(x_test), 100, 100, 3)
        y_test = y_test.reshape(len(y_test), 1)
```

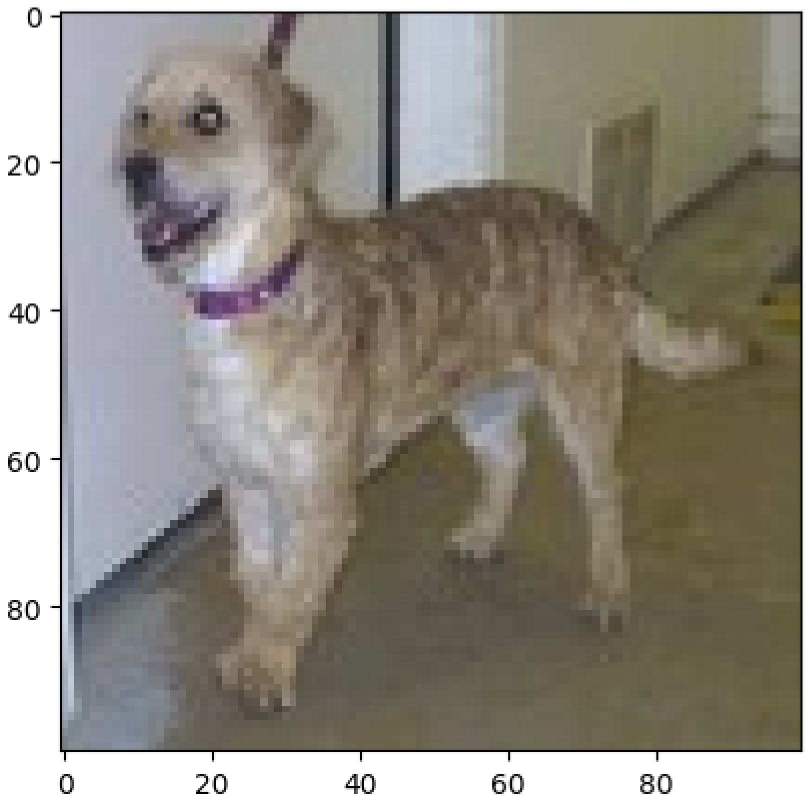
```
In [10]: # data after reshaping
         print('Shape of the data after reshaping:')
         print(x_train.shape)
         print(y_train.shape)
         print(x_test.shape)
         print(y_test.shape)
```

```
Shape of the data after reshaping:
(2000, 100, 100, 3)
(2000, 1)
(400, 100, 100, 3)
(400, 1)
```

```
In [11]: # Data scaling
         x_train = x_train/255.0
         x_test = x_test/255.0
```

```
In [12]: # printing the first image
plt.imshow(x_train[355, :])
plt.show()

# print the target for the first image
print('The target label is:', y_train[355])
```




```
The target label is: [0.]
```

CNN Model Building

```
In [13]: # import deep learning libraries
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import train_test_split
import keras
from keras.applications import MobileNetV2
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from keras.models import Model
from keras.layers import GlobalAveragePooling2D, Dense, Dropout
```

```
In [14]: # Creating a validation split
x_train_new, x_val, y_train_new, y_val = train_test_split(x_train, y_train, te
```

```
In [15]: base_model = MobileNetV2(
    weights='imagenet',
    include_top=False,
    input_shape=(100, 100, 3)
```

```
)

base_model.trainable = False
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applicati
ons/mobilenet_v2/mobilenet_v2_weights_tf_dim_ordering_tf_kernels_1.0_224_no_to
p.h5
9406464/9406464 ━━━━━━━━━━━━━━━━━━━━ 0s 0us/step
```

In [16]:
```
#Adding a clean classifier head
x = base_model.output
x = GlobalAveragePooling2D()(x)
x = Dense(128, activation='relu')(x)
x = Dropout(0.5)(x)
output = Dense(1, activation='sigmoid')(x)

model = Model(inputs=base_model.input, outputs=output)
```

In [17]:
```
# Compiling the model
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy
```

In [18]:
```
# Adding data augmentation
datagen = ImageDataGenerator(
    rotation_range=20,
    width_shift_range=0.1,
    height_shift_range=0.1,
    zoom_range=0.2,
    horizontal_flip=True
)

datagen.fit(x_train_new)
```

In [19]:
```
# training the model with the data
history = model.fit(datagen.flow(x_train_new, y_train_new, batch_size=32), epo
```

```
Epoch 1/10
57/57 ━━━━━━━━━━━━━━━━━━━━ 44s 471ms/step - accuracy: 0.7416 - loss: 0.5790 - v
al_accuracy: 0.8750 - val_loss: 0.2534
Epoch 2/10
57/57 ━━━━━━━━━━━━━━━━━━━━ 5s 81ms/step - accuracy: 0.8562 - loss: 0.3001 - va
l_accuracy: 0.9000 - val_loss: 0.2434
Epoch 3/10
57/57 ━━━━━━━━━━━━━━━━━━━━ 6s 101ms/step - accuracy: 0.8903 - loss: 0.2526 - va
l_accuracy: 0.9000 - val_loss: 0.2434
Epoch 4/10
57/57 ━━━━━━━━━━━━━━━━━━━━ 4s 75ms/step - accuracy: 0.8876 - loss: 0.2445 - va
l_accuracy: 0.9050 - val_loss: 0.2683
Epoch 5/10
57/57 ━━━━━━━━━━━━━━━━━━━━ 4s 75ms/step - accuracy: 0.9251 - loss: 0.1990 - va
l_accuracy: 0.9000 - val_loss: 0.2521
Epoch 6/10
57/57 ━━━━━━━━━━━━━━━━━━━━ 6s 99ms/step - accuracy: 0.8974 - loss: 0.2279 - va
l_accuracy: 0.9100 - val_loss: 0.2523
Epoch 7/10
57/57 ━━━━━━━━━━━━━━━━━━━━ 4s 74ms/step - accuracy: 0.9081 - loss: 0.2210 - va
l_accuracy: 0.9200 - val_loss: 0.2489
Epoch 8/10
57/57 ━━━━━━━━━━━━━━━━━━━━ 5s 82ms/step - accuracy: 0.9040 - loss: 0.1974 - va
l_accuracy: 0.8950 - val_loss: 0.2767
Epoch 9/10
57/57 ━━━━━━━━━━━━━━━━━━━━ 5s 90ms/step - accuracy: 0.9023 - loss: 0.2042 - va
l_accuracy: 0.8950 - val_loss: 0.2667
Epoch 10/10
57/57 ━━━━━━━━━━━━━━━━━━━━ 4s 75ms/step - accuracy: 0.9147 - loss: 0.1919 - va
l_accuracy: 0.9250 - val_loss: 0.2677
```

In [20]:

```python
# evaluating the model
model.evaluate(x_test, y_test)
```

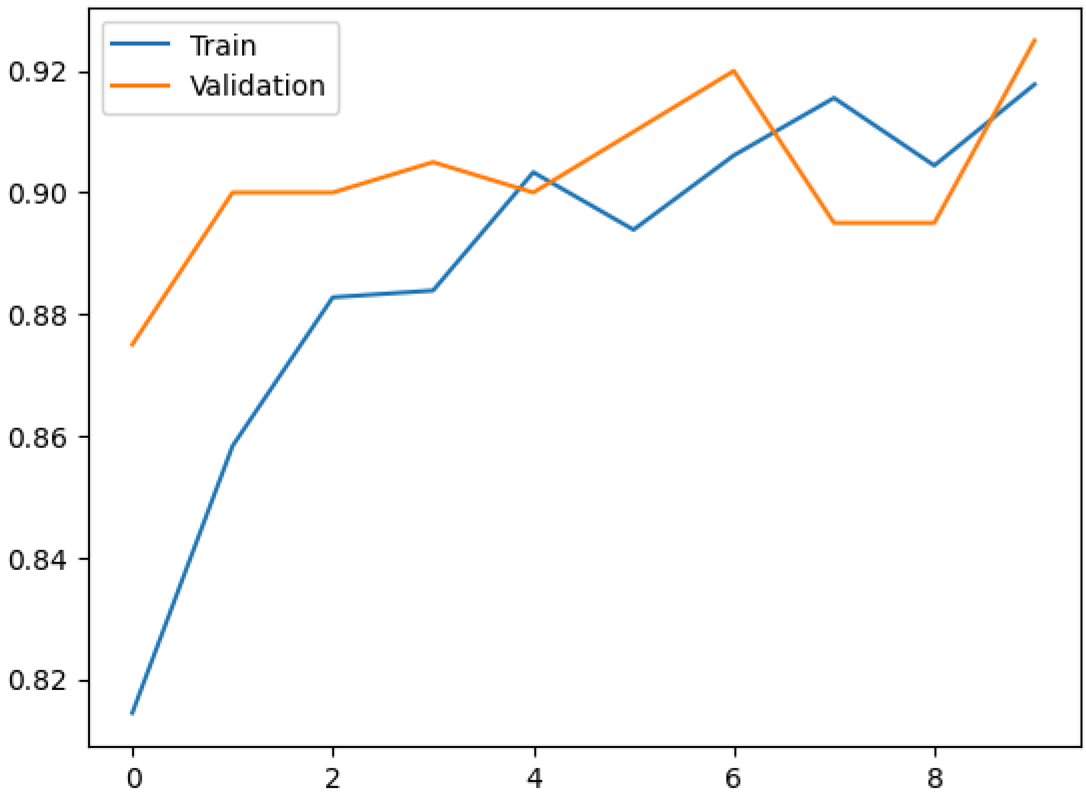
```
13/13 ━━━━━━━━━━━━━━━━━━━━ 10s 817ms/step - accuracy: 0.9119 - loss: 0.2116
```

Out[20]:

```
[0.21065618097782135, 0.9175000190734863]
```

In [21]:

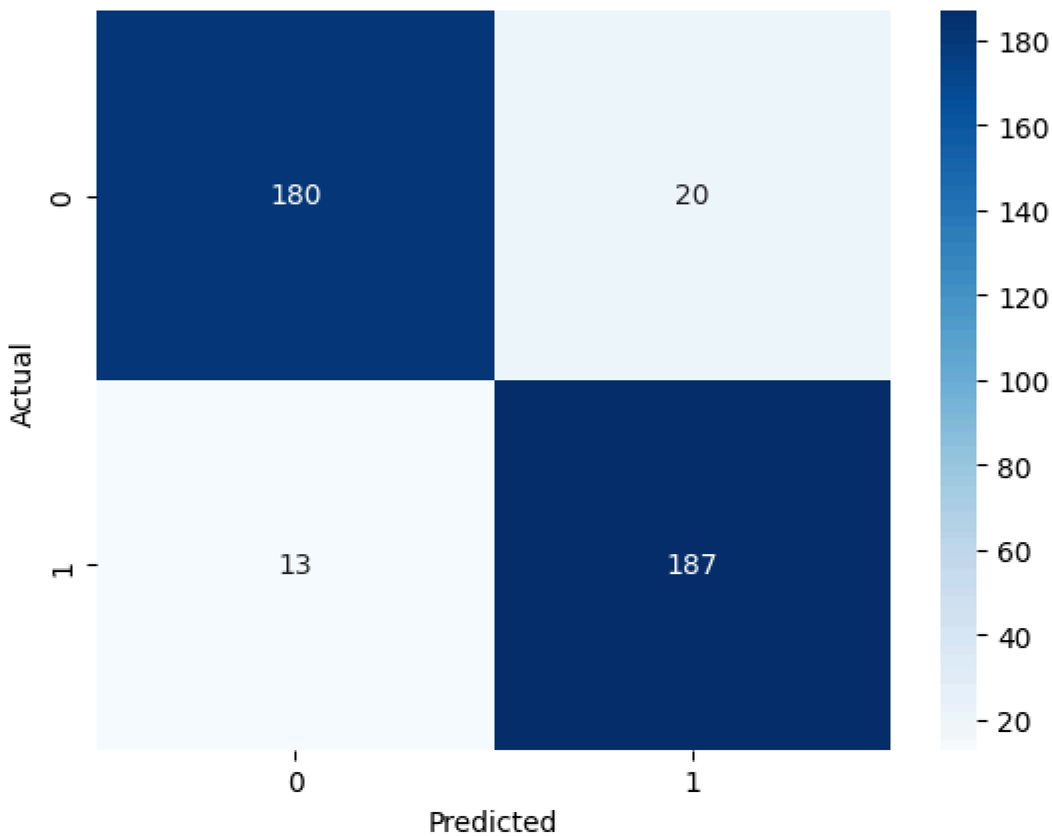
```python
# Training vs validation accuracy
plt.plot(history.history['accuracy'], label='Train')
plt.plot(history.history['val_accuracy'], label='Validation')
plt.legend()
plt.show()
```



In [22]:
```
# Confusion matrix
y_prob = model.predict(x_test)
y_pred = (y_prob >= 0.5).astype(int).reshape(-1)
cm = confusion_matrix(y_test.reshape(-1), y_pred)

sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```

```
13/13 ━━━━━━━━━━━━━━━━━━━━ 8s 350ms/step
```



In [23]:
```
# trainng data distribution of target
unique, counts = np.unique(y_train, return_counts=True)
print(unique, counts)
```

```
[0. 1.] [1000 1000]
```

In [24]:
```
len(x_test)
```

Out[24]:
```
400
```

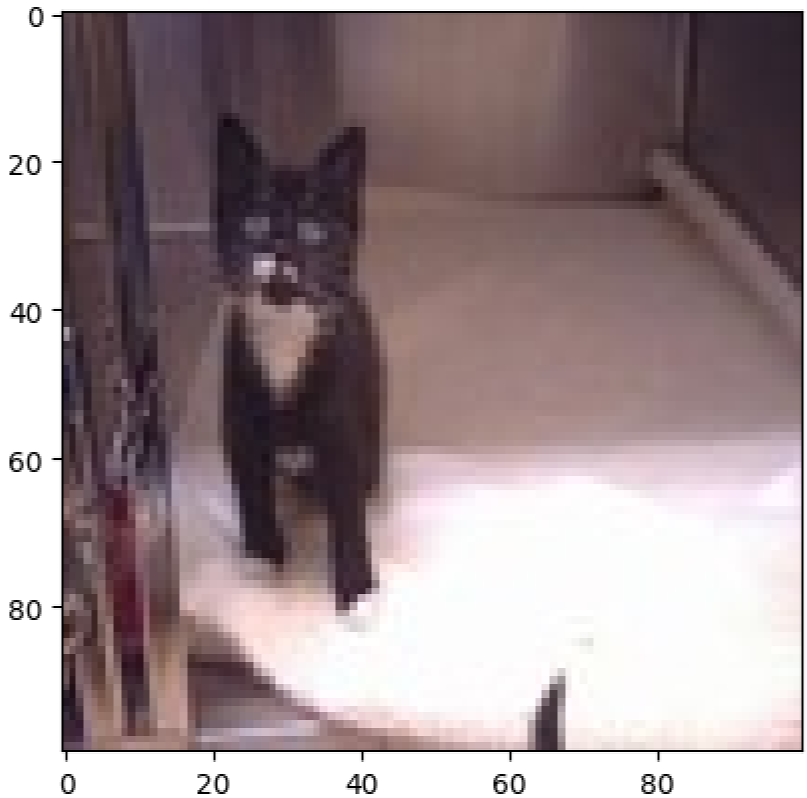
In [26]:
```
# predictions
rdm_img = random.randint(0, len(x_test))
plt.imshow(x_test[rdm_img, :])
plt.show()

# actual condition
if y_test[rdm_img, :] == 0:
    actual = 'Dog'
else:
    actual = 'Cat'

# prediction for the given image
y_pred = model.predict(x_test[rdm_img, :].reshape(1, 100, 100, 3))
print('Prediction Probability:', y_pred)

if y_pred >= 0.5:
    pred = 'Cat'
```

```
else:
    pred = 'Dog'
print('The actual image is:', actual)
print('The model has predicted as:', pred)
print('The image value',rdm_img)
```




```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 33ms/step
Prediction Probability: [[0.9878637]]
The actual image is: Cat
The model has predicted as: Cat
The image value 248
```

Final Conclusion & Limitations

Final Conclusion

I have used MobileNetV2 for binary image classification (cats vs dogs), the model achieved ~92% test accuracy and showed stable training–validation behavior. The results confirm that leveraging pretrained CNNs can deliver strong performance even with a relatively small dataset, making this approach practical and efficient for real-world image classification tasks.

Limitations

- The dataset is small and controlled, so performance may drop on real-world images with different lighting, backgrounds, or breeds.
- Only the classifier head was trained; the base model was not fine-tuned, which may limit peak performance.
- This setup handles binary classification only and would need architectural changes for multi-class problems.

In [25]:

```

```