Implementation of CNN on Cat-Dog classification



A Project Report in partial fulfillment of the degree

Bachelor of Technology in Computer Science & Artificial Intelligence By

Roll No	Name of the Student	
2203A52057	T. Navya Lohitha	

School of Computer Science & Artificial Intelligence

SR University, Ananthsagar, Hasanparthy (M), Warangal, Telangana 506371, India

2024-25

DATASET DESCRIPTION

• **Dataset Name:** Dogs vs. Cats

• Source: Kaggle

• Content: The dataset consists of images of dogs and cats, where each image belongs to one of the two classes (Dog or Cat). These images are labeled as either "cat" or "dog" based on the animal in the image.

The dataset has a total of:

25,000 training images

12,500 test images

• **Image Size**: The images are in JPEG format and have varying dimensions. Most of them are resized to fit a neural network's input requirements.

Objective:

The goal of this dataset is to build a model that can predict whether an image contains a cat or a dog.

The binary classification task can be tackled using deep learning models such as CNNs

(Convolutional Neural Networks), which are well-suited for image classification tasks.

Steps to Approach the Problem:

1. Data Preprocessing:

- Resize the images to a consistent size, such as 150x150 or 224x224 pixels.
- Normalize the pixel values to the range [0, 1] by dividing by 255.
- Split the dataset into training, validation, and test sets (if not already split).

2. Model Building:

- Use a Convolutional Neural Network (CNN), which is the most commonly used deep learning model for image classification tasks.
- The architecture can consist of several convolutional layers followed by pooling layers, and eventually fully connected layers.

3. Training:

- Use binary cross-entropy as the loss function, as it's a binary classification problem.
- Use accuracy as the evaluation metric.
- Implement data augmentation to make the model more robust and prevent overfitting.

4. Evaluation:

- Evaluate the model on the test set.
- Analyze metrics like accuracy, precision, recall, and F1-score.

Implementation:

Code was implemnted in Kaggle Environement

1. Loading Libraries

```
# Basic
import os
from os import makedirs, listdir
from shutil import copyfile
from random import seed, random
import numpy as np
import pandas as pd
# Visuals
import seaborn as sns
import matplotlib.pyplot as plt
from matplotlib.image import imread
from PIL import Image
# Scikit-learn
from sklearn.model_selection import train_test_split
from \ sklearn.metrics \ import\ classification\_report, confusion\_matrix, ConfusionMatrix Display
# Tensorflow
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.layers import Dense, MaxPooling2D, Dropout, Flatten, BatchNormalization,
Conv2D
from tensorflow.keras.callbacks import ReduceLROnPlateau, EarlyStopping
```

2. Data Extraction and Analysis

labels = cat_labels + dog_labels

print(len(labels))

```
import os
cat = os.listdir('/kaggle/input/PetImages/Cat')
dog = os.listdir('/kaggle/input/PetImages/Dog')
print("Cat:", cat[:5])
print("Dog:", dog[:5])

count images

print(len(cat))
print(len(dog))

Create lables
cat_labels = [1] * 12499
dog_labels = [0] * 12499
```

Display Sample Images

```
img = mpimg.imread('/kaggle/input/dog-and-cat-classification-dataset/PetImages/Cat/0.jpg') \\ plt.imshow(img) \\ plt.show() \\ img = mpimg.imread('/kaggle/input/dog-and-cat-classification-dataset/PetImages/Dog/0.jpg') \\ plt.imshow(img) \\ plt.show()
```

3. Data Preprocessing

Convert Images to Numpy Arrays

```
from PIL import Image
import numpy as np
data = []
# Cat Images
cat_path = '/kaggle/input/dog-and-cat-classification-dataset/PetImages/Cat/'
for img_file in cat:
  image = Image.open(cat_path + img_file).resize((128, 128)).convert('RGB')
  data.append(np.array(image))
# Dog Images
dog_path = '/kaggle/input/dog-and-cat-classification-dataset/PetImages/Dog/'
for img file in dog:
  image = Image.open(dog_path + img_file).resize((128, 128)).convert('RGB')
  data.append(np.array(image))
x = np.array(data)
y = np.array(labels)
Train-Test Split and Scaling data
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=2)
x_{train}scal = x_{train} / 255
```

4. Model Development

 $x_{test_scal} = x_{test} / 255$

```
model = Sequential()
model.add(Conv2D(32, kernel_size=(3, 3), activation='relu', input_shape=(128, 128, 3)))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(64, kernel_size=(3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
```

```
model.add(Dense(128, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(64, activation='relu'))
model.add(Dropout(0.5))
model.add(Dropout(0.5))
model.add(Dense(2, activation='sigmoid'))
model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['acc'])
model.fit(x_train_scal, y_train, validation_split=0.1, epochs=30)
model.save("cat_dog_model.h5")
```

5. Prediction

```
input_image_path = input('Path of the image to be predicted: ')
input_image = cv2.imread(input_image_path)
cv2_imshow(input_image)
input_image_resized = cv2.resize(input_image, (128, 128))
input_image_scaled = input_image_resized / 255
input_image_reshaped = np.reshape(input_image_scaled, [1, 128, 128, 3])
input_prediction = model.predict(input_image_reshaped)
input_pred_label = np.argmax(input_prediction)
if input_pred_label == 1:
    print('The person in the image is wearing a mask')
else:
    print('The person in the image is not wearing a mask')
```

RESULTS

Loading images

```
import os

cat = os.listdir('/kaggle/input/PetImages/Cat')
dog = os.listdir('/kaggle/input/PetImages/Dog')
|
print("Cat:", cat[:5])
print("Dog:", dog[:5])

Cat: ['7981.jpg', '6234.jpg', '1269.jpg', '3863.jpg', '6241.jpg']
Dog: ['7981.jpg', '6234.jpg', '1269.jpg', '3863.jpg', '6241.jpg']
```

Data Extraction and Analysis

```
print(len(cat))
print(len(dog))

12499
12499
```

```
cat_labels = [1]*12499
dog_labels = [0]*12499
```

```
print(cat_labels[:5])
print(dog_labels[:5])
```

```
[1, 1, 1, 1, 1]
[0, 0, 0, 0, 0]
```

```
labels =cat_labels + dog_labels
print(len(labels))
```

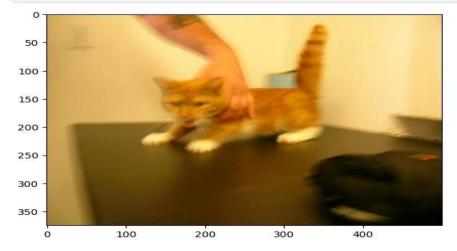
24998

```
print(labels[:5])
print(labels[-5:])

[1, 1, 1, 1, 1]
[0, 0, 0, 0, 0]
```

```
import matplotlib.pyplot as plt
import matplotlib.image as mpimg # import the module

img = mpimg.imread('/kaggle/input/PetImages/Cat/0.jpg') # Now mpimg is defined and can be used
imgplot = plt.imshow(img)
plt.show()
```



```
import matplotlib.pyplot as plt
import matplotlib.image as mpimg # import the module

img = mpimg.imread('/kaggle/input/PetImages/Dog/0.jpg') # Now mpimg is defined and can be used
imgplot = plt.imshow(img)
plt.show()
```



model.summary()

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 126, 126, 32)	896
max_pooling2d (MaxPooling2D)	(None, 63, 63, 32)	0
conv2d_1 (Conv2D)	(None, 61, 61, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 30, 30, 64)	0
flatten (Flatten)	(None, 57600)	0
dense (Dense)	(None, 128)	7,372,928
dropout (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 64)	8,256
dropout_1 (Dropout)	(None, 64)	0
dense_2 (Dense)	(None, 2)	130

Total params: 7,400,706 (28.23 MB)

Trainable params: 7,400,706 (28.23 MB)

Non-trainable params: 0 (0.00 B)

MODEL TRAINING

<keras.src.callbacks.history.History at 0x78667c277520>

Epoch 1/30 /usr/local/lib/python3.10/dist-packages/keras/src/trainers/data adapters/py dataset adapter.py:122: UserWarning: Your 'PyDataset' class should call 'super(). init they will be ignored. self._warn_if_super_not_called() - 79s 132ms/step - accuracy: 0.6884 - loss: 0.6158 - val accuracy: 0.7379 - val loss: 0.5728 - learning rate: 0.0010 563/563 Epoch 2/30 - 70s 123ms/step - accuracy: 0.7178 - loss: 0.5840 - val_accuracy: 0.7384 - val_loss: 0.5533 - learning rate: 0.0010 563/563 Epoch 3/30 563/563 70s 123ms/step - accuracy: 0.7276 - loss: 0.5658 - val_accuracy: 0.7129 - val_loss: 0.5867 - learning_rate: 0.0010 Epoch 4/30 563/563 70s 123ms/step - accuracy: 0.7368 - loss: 0.5483 - val_accuracy: 0.7409 - val_loss: 0.5253 - learning_rate: 0.0010 Epoch 5/30 75s 131ms/step - accuracy: 0.7474 - loss: 0.5300 - val_accuracy: 0.7394 - val_loss: 0.5252 - learning rate: 0.0010 563/563 Epoch 6/30 563/563 75s 132ms/step - accuracy: 0.7524 - loss: 0.5174 - val_accuracy: 0.7574 - val_loss: 0.5054 - learning_rate: 0.0010 Epoch 7/30 563/563 -70s 124ms/step - accuracy: 0.7525 - loss: 0.5132 - val_accuracy: 0.7674 - val_loss: 0.4908 - learning_rate: 0.0010 Epoch 8/30 563/563 -75s 131ms/step - accuracy: 0.7569 - loss: 0.5085 - val_accuracy: 0.7509 - val_loss: 0.5073 - learning rate: 0.0010 Epoch 9/30 563/563 • 70s 122ms/step - accuracy: 0.7624 - loss: 0.4996 - val_accuracy: 0.7869 - val_loss: 0.4758 - learning_rate: 0.0010 Epoch 10/30 73s 128ms/step - accuracy: 0.7773 - loss: 0.4830 - val accuracy: 0.7924 - val loss: 0.4616 - learning rate: 0.0010 563/563 • Epoch 11/30 563/563 -75s 132ms/step - accuracy: 0.7769 - loss: 0.4813 - val_accuracy: 0.7909 - val_loss: 0.4667 - learning_rate: 0.0010 Epoch 12/30 - 72s 126ms/step - accuracy: 0.7817 - loss: 0.4694 - val_accuracy: 0.7864 - val_loss: 0.4635 - learning_rate: 0.0010 563/563 -Epoch 13/30 563/563 - 71s 125ms/step - accuracy: 0.7819 - loss: 0.4707 - val_accuracy: 0.7779 - val_loss: 0.4774 - learning_rate: 0.0010 Epoch 14/30 563/563 71s 125ms/step - accuracy: 0.7932 - loss: 0.4554 - val_accuracy: 0.8209 - val_loss: 0.4291 - learning_rate: 2.0000e-04 Epoch 15/30 563/563 - 75s 132ms/step - accuracy: 0.8045 - loss: 0.4408 - val accuracy: 0.8109 - val loss: 0.4339 - learning rate: 2.0000e-04 Epoch 16/30 563/563 - 75s 133ms/step - accuracy: 0.8085 - loss: 0.4274 - val accuracy: 0.8149 - val loss: 0.4217 - learning rate: 2.0000e-04 Epoch 17/30 563/563 72s 126ms/step - accuracy: 0.8127 - loss: 0.4235 - val accuracy: 0.8074 - val loss: 0.4305 - learning rate: 2.0000e-04 Epoch 18/30 563/563 -- 73s 128ms/step - accuracy: 0.8091 - loss: 0.4261 - val accuracy: 0.8129 - val loss: 0.4298 - learning rate: 2.0000e-04 Epoch 19/30 563/563 73s 127ms/step - accuracy: 0.8086 - loss: 0.4275 - val_accuracy: 0.8074 - val_loss: 0.4237 - learning_rate: 2.0000e-04 Epoch 20/30 563/563 71s 124ms/step - accuracy: 0.8152 - loss: 0.4160 - val_accuracy: 0.8134 - val_loss: 0.4174 - learning_rate: 4.0000e-05 Epoch 21/30 563/563 71s 124ms/step - accuracy: 0.8149 - loss: 0.4261 - val_accuracy: 0.8144 - val_loss: 0.4177 - learning_rate: 4.0000e-05 Epoch 22/30 563/563 73s 129ms/step - accuracy: 0.8178 - loss: 0.4190 - val_accuracy: 0.8139 - val_loss: 0.4220 - learning_rate: 4.0000e-05 Epoch 23/30 563/563 70s 123ms/step - accuracy: 0.8202 - loss: 0.4180 - val_accuracy: 0.8069 - val_loss: 0.4250 - learning_rate: 4.0000e-05 Epoch 24/30 563/563 70s 122ms/step - accuracy: 0.8130 - loss: 0.4230 - val_accuracy: 0.8084 - val_loss: 0.4089 - learning_rate: 8.0000e-06 Epoch 25/30 563/563 68s 120ms/step - accuracy: 0.8169 - loss: 0.4114 - val accuracy: 0.8054 - val loss: 0.4225 - learning rate: 8.0000e-06 Epoch 26/30 563/563 • 72s 126ms/step - accuracy: 0.8255 - loss: 0.4032 - val accuracy: 0.8244 - val loss: 0.4084 - learning rate: 8.0000e-06 Epoch 27/30 563/563 71s 125ms/step - accuracy: 0.8216 - loss: 0.4068 - val accuracy: 0.8084 - val loss: 0.4094 - learning rate: 8.0000e-06 Epoch 28/30 563/563 70s 123ms/step - accuracy: 0.8154 - loss: 0.4195 - val_accuracy: 0.8114 - val_loss: 0.4160 - learning_rate: 8.0000e-06 Epoch 29/30 563/563 71s 125ms/step - accuracy: 0.8170 - loss: 0.4165 - val_accuracy: 0.8234 - val_loss: 0.4064 - learning_rate: 8.0000e-06 Epoch 30/30 563/563 - 73s 128ms/step - accuracy: 0.8224 - loss: 0.4049 - val_accuracy: 0.8194 - val_loss: 0.4092 - learning_rate: 8.0000e-06

PREDICTION:

```
import cv2
import numpy as np
import matplotlib.pyplot as plt
from tensorflow.keras.models import load_model
# Load saved model
model = load_model('model.h5')
# Input image path
input_image_path = input('Path of the image to be predicted: ')
# Read and display
input_image = cv2.imread(input_image_path)
input_image_rgb = cv2.cvtColor(input_image, cv2.COLOR_BGR2RGB)
plt.imshow(input_image_rgb)
plt.axis('off')
plt.title('Input Image')
plt.show()
# Preprocessing
input_image_resized = cv2.resize(input_image, (128,128))
input_image_scaled = input_image_resized / 255.0
input_image_reshaped = np.reshape(input_image_scaled, [1,128,128,3])
input_prediction = model.predict(input_image_reshaped)
print("Prediction Probability:", input_prediction[0][0])
# Binary Classification (\theta = Dog, T = Cat)
input_pred_label = (input_prediction[0][0] > 0.5).astype(int)
if input_pred_label == 1:
    print('The animal in the image is a **Cat**')
else:
    print('The animal in the image is a **Dog**')
```

Path of the image to be predicted: /kaggle/input/dog-and-cat-classification-dataset/PetImages/Dog/10014.jpg

Input Image



1/1 —— 0s 225ms/step Prediction Probability: 0.09162871 The animal in the image is a **Dog**

```
import cv2
import numpy as np
import matplotlib.pyplot as plt
from tensorflow.keras.models import load_model
# Load saved model
model = load_model('model.h5')
# Input image path
input_image_path = input('Path of the image to be predicted: ')
# Read and display
input_image = cv2.imread(input_image_path)
input_image_rgb = cv2.cvtColor(input_image, cv2.COLOR_BGR2RGB)
plt.imshow(input_image_rgb)
plt.axis('off')
plt.title('Input Image')
plt.show()
# Preprocessing
input_image_resized = cv2.resize(input_image, (128,128))
input_image_scaled = input_image_resized / 255.0
input_image_reshaped = np.reshape(input_image_scaled, [1,128,128,3])
# Predict
input_prediction = model.predict(input_image_reshaped)
print("Prediction Probability:", input_prediction[0][0])
# Binary Classification (\theta = Dog, 1 = Cat)
input\_pred\_label = (input\_prediction[0][0] > 0.5).astype(int)
if input_pred_label == 1:
    print('The animal in the image is a **Cat**')
else:
    print('The animal in the image is a **Dog**')
```

Path of the image to be predicted: /kaggle/input/dog-and-cat-classification-dataset/PetImages/Cat/100.jpg
Input Image



1/1 — 0s 222ms/step Prediction Probability: 0.5203394 The animal in the image is a **Cat**