MSDS Module 8 Dogs vs. Cats Redux: Kernel Edition

This project involves the classification of images of cats and dogs using a Convolutional Neural Network (CNN) built with TensorFlow and Keras. The entire process includes data preparation, model building, training, evaluation, and prediction. Here is a detailed summary of the code and the results:

Data Preparation

1. Importing Libraries: Various libraries are imported for handling data manipulation (Pandas, Numpy), visualization (Seaborn, Matplotlib), image processing (PIL), and machine learning (Scikit-learn, TensorFlow).

2. Extracting Zip Files: The training and testing datasets are extracted from zip files using the zipfile module. The images are stored in directories for further processing.

3. Loading Data into a DataFrame: The filenames of the images are listed and their corresponding labels (cat or dog) are extracted from the filenames. This information is stored in a Pandas DataFrame.

4. Visualizing Images: A few images of cats and dogs are displayed using Matplotlib to understand the dataset visually.

5. Train-Test Split: The data is split into training and testing sets using Scikit-learn's train_test_split method. This split ensures that 80% of the data is used for training and 20% for testing.

6. Class Distribution: The distribution of classes (cats and dogs) in the training and testing sets is visualized using Seaborn.

Image Data Generation

1. Image Data Generators: ImageDataGenerator from Keras is used to preprocess the images. This includes rescaling the pixel values to a range of 0 to 1.
2. Creating Data Generators: Data generators are created for both training and testing datasets. These generators flow from the respective directories and handle image loading and preprocessing.

Model Building

1. CNN Architecture: A Sequential model is built using Keras. The model consists of the following layers:
    - Convolutional layers with ReLU activation and Batch Normalization.
    - MaxPooling layers for down-sampling.
    - Dropout layers for regularization to prevent overfitting.
    - A Flatten layer to convert the 2D matrices into a 1D vector.
    - Dense (fully connected) layers with ReLU activation.
    - An output layer with Softmax activation for binary classification.
2. Model Compilation: The model is compiled using the Adam optimizer, binary cross-entropy loss function, and accuracy as the evaluation metric.
3. Callbacks: A ReduceLROnPlateau callback is used to reduce the learning rate when the validation accuracy plateaus.

Training the Model

1. Model Training: The model is trained for 15 epochs using the training data generator and validated against the testing data generator.
2. Training Logs: The accuracy and loss for both training and validation sets are recorded. The learning rate is adjusted based on the validation accuracy.

Results

1. Training and Validation Performance: The model achieves high accuracy on the training data (99.78%) but a lower accuracy on the test data (81.84%). This discrepancy suggests overfitting.
2. Loss and Accuracy Curves: The loss and accuracy curves for both training and validation data are plotted, showing the training dynamics over epochs.
3. Confusion Matrix and Classification Report: The confusion matrix and classification report provide detailed performance metrics such as precision, recall, and F1-score for both classes (cats and dogs).

Evaluation and Prediction

1. Model Evaluation: The model is evaluated on both the training and testing datasets to report final accuracy and loss.
2. Saving the Model: The trained model is saved for future use.

3. Predictions on Test Images: The model is used to predict the classes of new images. A function is defined to preprocess and predict the class of a single image. Sample predictions are visualized to show the model's performance.

Result

We achieved log loss score of 0.91794 on Kaggle test dataset. The result can definitely be improved as we are having overfitting issue. Our model can be improved by reducing the model complexity. We can use data augmentation to increases the diversity of training data by applying random transformations such as rotations, translations, flipping, zooming, and more. We can reduce training epoch, stop early, and , use different activation function. We can also reduce the number of layers or the number of units in each layer and apply dropout Layers techniques (randomly turn off some neurons during training).

Appendix

In [3]:
```python
import os
import numpy as np
import pandas as pd

# visuals
import seaborn as sns
import matplotlib.pyplot as plt
from matplotlib.image import imread # Used to read images
from PIL import Image # Image Visulization

# Scikit-Learn
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report,confusion_matrix,ConfusionMatrixDisplay

# 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
```

Unzip File and Load Train Dataset into dataframe

In [8]:
```python
train_path = "C:/Users/zhaox/Northwestern HW/CatDog/train.zip"
test_path = "C:/Users/zhaox/Northwestern HW/CatDog/test.zip"

files = "C:/Users/zhaox/Northwestern HW/CatDog"

# zipfile - python module for extracting files from a zip file
import zipfile

with zipfile.ZipFile(train_path, 'r') as zipp:
    zipp.extractall(files)

with zipfile.ZipFile(test_path, 'r') as zipp:
    zipp.extractall(files)
```

In [4]:
```python
image_dir = "C:/Users/zhaox/Northwestern HW/CatDog/train/"

filenames = os.listdir(image_dir)
labels = [x.split(".")[0] for x in filenames]

data = pd.DataFrame({"filename": filenames, "label": labels})

data.head()
```

Out[4]:

	filename	label
0	cat.0.jpg	cat
1	cat.1.jpg	cat
2	cat.10.jpg	cat
3	cat.100.jpg	cat
4	cat.1000.jpg	cat

In [5]:
```python
data.label.value_counts()
```

Out[5]:
```
cat    12500
dog    12500
Name: label, dtype: int64
```

In [6]:

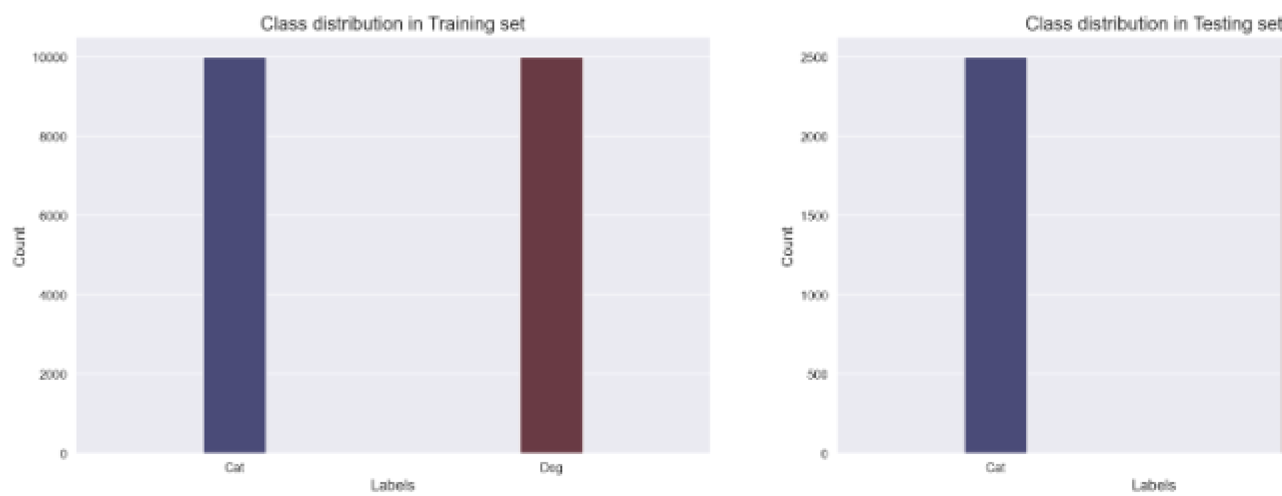
```
plt.figure(figsize=(20,20)) # specifying the overall grid size
plt.subplots_adjust(hspace=0.4)


for i in range(5):

    plt.subplot(10, 14,i+1)    # the number of images in the grid is 10*10 (100)
    filename = 'train/' + 'dog.' + str(i) + '.jpg'
    image = imread(filename)
    plt.imshow(image)
    plt.title('Dog',fontsize=12)
    plt.axis('off')

plt.show()


plt.figure(figsize=(20,20)) # specifying the overall grid size
plt.subplots_adjust(hspace=0.4)


for i in range(5):

    plt.subplot(10, 14,i+1)    # the number of images in the grid is 10*10 (100)
    filename = 'train/' + 'cat.' + str(i) + '.jpg'
    image = imread(filename)
    plt.imshow(image)
    plt.title('Cat',fontsize=12)
    plt.axis('off')

plt.show()
```

Split Train Test and Image Transition

In [7]:
```
# train test split using dataframe

labels = data['label']

# 20% split
# 80%.    20%
X_train, X_test = train_test_split(data, test_size=0.2, stratify=labels, random_state = 42)

label_test_val = X_test['label']

print('The shape of train data',X_train.shape)
print('The shape of test data',X_test.shape)
```

```
The shape of train data (20000, 2)
The shape of test data (5000, 2)
```

In [8]:
```
labels = ['Cat','Dog']

label1,count1 = np.unique(X_train.label,return_counts=True)
label2,count2 = np.unique(X_test.label,return_counts=True)

uni1 = pd.DataFrame(data=count1,index=labels,columns=['Count1'])
uni2 = pd.DataFrame(data=count2,index=labels,columns=['Count2'])


plt.figure(figsize=(20,6),dpi=200)
sns.set_style('darkgrid')

plt.subplot(121)
sns.barplot(data=uni1,x=uni1.index,y='Count1',palette='icefire',width=0.2).set_title('Class distribution in Tra
plt.xlabel('Labels',fontsize=12)
plt.ylabel('Count',fontsize=12)


plt.subplot(122)
sns.barplot(data=uni2,x=uni2.index,y='Count2',palette='icefire',width=0.2).set_title('Class distribution in Tes
plt.xlabel('Labels',fontsize=12)
plt.ylabel('Count',fontsize=12)

plt.show()
```



```
In [9]: # parameters
image_size = 128 # Size of the image
image_channel = 3 # Colour scale (RGB)
bat_size = 32 # Number of files/images processed at once
```

```
In [10]: # Creating image data generator
# Preprocess images ==> Feature Engineering for Images
train_datagen = ImageDataGenerator(rescale=1./255)

test_datagen = ImageDataGenerator(rescale=1./255)
```

```
In [11]: # Applying image data gernerator to train and test data

train_generator = train_datagen.flow_from_dataframe(X_train,
                                                    directory = 'C:/Users/zhaox/Northwestern HW/CatDog/train/',
                                                    x_col= 'filename',
                                                    y_col= 'label',
                                                    batch_size = bat_size,
                                                    target_size = (image_size,image_size)
                                                   )


test_generator = test_datagen.flow_from_dataframe(X_test,
                                                  directory = 'C:/Users/zhaox/Northwestern HW/CatDog/train/',
                                                  x_col= 'filename',
                                                  y_col= 'label',
                                                  batch_size = bat_size,
                                                  target_size = (image_size,image_size),
                                                  shuffle=False
                                                 )
```

```
Found 20000 validated image filenames belonging to 2 classes.
Found 5000 validated image filenames belonging to 2 classes.
```

```
In [ ]: # train_gen = train_datagen.flow_from_directory('C:/Users/zhaox/Northwestern HW/CatDog/train/',
#                                               class_mode='binary',
#                                               target_size = (image_size,image_size),
#                                               batch_size = bat_size,
#                                              )

# test_gen = test_datagen.flow_from_directory('C:/Users/zhaox/Northwestern HW/CatDog/train/',
#                                         class_mode='binary',
#                                         batch_size = bat_size,
#                                         target_size = (image_size,image_size),
#                                         shuffle = False
#                                        )
```

Modeling

In [12]:
```
model = Sequential()

# Input Layer
model.add(Conv2D(32,(3,3),activation='relu',input_shape = (image_size,image_size,image_channel)))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Dropout(0.2))

# Block 1
model.add(Conv2D(64,(3,3),activation='relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Dropout(0.2))


# Fully Connected layers
model.add(Flatten())
model.add(Dense(512,activation='relu'))
model.add(BatchNormalization())
model.add(Dropout(0.2))

# Output layer
model.add(Dense(2,activation='softmax')) # Softmax for binary classification

model.summary()
```

```
C:\Users\zhaox\anaconda3\lib\site-packages\keras\src\layers\convolutional\base_conv.py:107: UserWarning: Do not p
shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as th
in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 126, 126, 32)	896
batch_normalization (BatchNormalization)	(None, 126, 126, 32)	128
max_pooling2d (MaxPooling2D)	(None, 63, 63, 32)	0
dropout (Dropout)	(None, 63, 63, 32)	0
conv2d_1 (Conv2D)	(None, 61, 61, 64)	18,496
batch_normalization_1 (BatchNormalization)	(None, 61, 61, 64)	256
max_pooling2d_1 (MaxPooling2D)	(None, 30, 30, 64)	0
dropout_1 (Dropout)	(None, 30, 30, 64)	0
flatten (Flatten)	(None, 57600)	0
dense (Dense)	(None, 512)	29,491,712
batch_normalization_2 (BatchNormalization)	(None, 512)	2,048
dropout_2 (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 2)	1,026

In [13]:
```
learning_rate_reduction = ReduceLROnPlateau(monitor = 'val_accuracy',
                                            patience=2,
                                            factor=0.1,
                                            min_lr = 0.00001,
                                            verbose = 1)

# early_stoping = EarlyStopping(monitor='val_loss',patience= 2,restore_best_weights=True,verbose=0)
```

In [14]:
```
model.compile(optimizer='adam',loss='binary_crossentropy',metrics=['accuracy'])
```

In [15]:
```
cat_dog = model.fit(train_generator,
                    validation_data = test_generator,
                    callbacks=[learning_rate_reduction],
                    epochs = 15,
                    # steps_per_epoch = len(train_generator),
                    # validation_steps = len(val_generaotor),
                   )
```

```
Epoch 1/15
```

```
C:\Users\zhaox\anaconda3\lib\site-packages\keras\src\trainers\data_adapters\py_dataset_adapter.py:121: UserWarnin
aset` class should call `super().__init__(**kwargs)` in its constructor. `**kwargs` can include `workers`, `use_m
`, `max_queue_size`. Do not pass these arguments to `fit()`, as they will be ignored.
  self._warn_if_super_not_called()
```

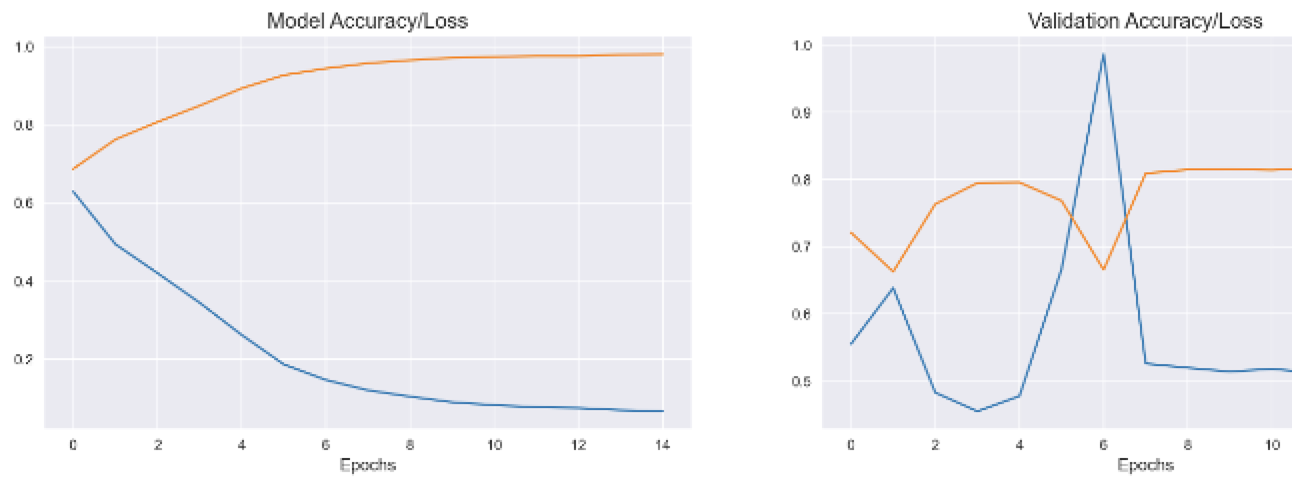
```
625/625 ━━━━━━━━━━━━━━━━━━━━ 151s 237ms/step - accuracy: 0.6487 - loss: 0.7349 - val_accuracy: 0.7208 - val_loss:
ning_rate: 0.0010
Epoch 2/15
625/625 ━━━━━━━━━━━━━━━━━━━━ 126s 201ms/step - accuracy: 0.7567 - loss: 0.5051 - val_accuracy: 0.6628 - val_loss:
ning_rate: 0.0010
Epoch 3/15
625/625 ━━━━━━━━━━━━━━━━━━━━ 124s 198ms/step - accuracy: 0.8063 - loss: 0.4213 - val_accuracy: 0.7634 - val_loss:
ning_rate: 0.0010
Epoch 4/15
625/625 ━━━━━━━━━━━━━━━━━━━━ 125s 200ms/step - accuracy: 0.8581 - loss: 0.3316 - val_accuracy: 0.7948 - val_loss:
ning_rate: 0.0010
Epoch 5/15
625/625 ━━━━━━━━━━━━━━━━━━━━ 125s 200ms/step - accuracy: 0.8965 - loss: 0.2562 - val_accuracy: 0.7956 - val_loss:
ning_rate: 0.0010
Epoch 6/15
625/625 ━━━━━━━━━━━━━━━━━━━━ 124s 198ms/step - accuracy: 0.9325 - loss: 0.1760 - val_accuracy: 0.7684 - val_loss:
ning_rate: 0.0010
Epoch 7/15
625/625 ━━━━━━━━━━━━━━━━━━━━ 0s 184ms/step - accuracy: 0.9499 - loss: 0.1354
Epoch 7: ReduceLROnPlateau reducing learning rate to 1.0000000474974514e-05.
625/625 ━━━━━━━━━━━━━━━━━━━━ 124s 198ms/step - accuracy: 0.9499 - loss: 0.1354 - val_accuracy: 0.6656 - val_loss:
ning_rate: 0.0010
Epoch 8/15
625/625 ━━━━━━━━━━━━━━━━━━━━ 125s 199ms/step - accuracy: 0.9537 - loss: 0.1281 - val_accuracy: 0.8092 - val_loss:
ning_rate: 1.0000e-05
Epoch 9/15
625/625 ━━━━━━━━━━━━━━━━━━━━ 125s 200ms/step - accuracy: 0.9608 - loss: 0.1131 - val_accuracy: 0.8146 - val_loss:
ning_rate: 1.0000e-05
Epoch 10/15
625/625 ━━━━━━━━━━━━━━━━━━━━ 126s 201ms/step - accuracy: 0.9730 - loss: 0.0867 - val_accuracy: 0.8152 - val_loss:
ning_rate: 1.0000e-05
Epoch 11/15
625/625 ━━━━━━━━━━━━━━━━━━━━ 126s 201ms/step - accuracy: 0.9728 - loss: 0.0833 - val_accuracy: 0.8140 - val_loss:
ning_rate: 1.0000e-05
Epoch 12/15
625/625 ━━━━━━━━━━━━━━━━━━━━ 125s 199ms/step - accuracy: 0.9767 - loss: 0.0754 - val_accuracy: 0.8168 - val_loss:
ning_rate: 1.0000e-05
Epoch 13/15
625/625 ━━━━━━━━━━━━━━━━━━━━ 126s 201ms/step - accuracy: 0.9741 - loss: 0.0793 - val_accuracy: 0.8172 - val_loss:
ning_rate: 1.0000e-05
Epoch 14/15
```

In [16]:
```
cat_dog.history
```

Out[16]:

```
{'accuracy': [0.687250018119812,
  0.7623000144958496,
  0.8069499731063843,
  0.8486499786376953,
  0.8931499719619751,
  0.9268500208854675,
  0.9441499710083008,
  0.9574000239372253,
  0.9650499820709229,
  0.9715499877929688,
  0.973550021648407,
  0.9761999845504761,
  0.9761000275611877,
  0.979200005531311,
  0.9804999828338623],
 'loss': [0.6284269690513611,
  0.494020015001297,
  0.4199835956096649,
  0.34429848194122314,
  0.261682182550430З,
  0.18631108105182648,
  0.14645017683506012,
  0.12000100314617157,
  0.10394812375307083,
  0.08940692245960236,
  0.0819661095738411,
  0.0765935406088829,
  0.07462987303733826,
  0.06912492960691452,
  0.06619978696107864],
 'val_accuracy': [0.72079998254776,
  0.6628000140190125,
  0.7634000182151794,
  0.7947999835014343,
  0.7955999970436096,
  0.7684000134468079,
  0.6656000018119812,
  0.8091999888420105,
  0.8145999908447266,
  0.8151999711990356,
  0.8140000104904175,
  0.8167999982833862,
  0.817200005054474,
  0.8181999921798706,
  0.8184000253677368],
 'val_loss': [0.555267870426178,
  0.6384783387184143,
  0.4827093183994293,
  0.45488378405570984,
  0.4775106906890869,
  0.6664386987686157,
  0.9865285158157349,
  0.5259643197059631,
  0.5196463465690613,
  0.5139132142066956,
  0.5180850625038147,
  0.5118813514709473,
  0.5123811364173889,
  0.514224112033844,
  0.5144171118736267],
 'learning_rate': [0.0010000000474974513,
  0.0010000000474974513,
```

```
In [17]: error = pd.DataFrame(cat_dog.history)

         plt.figure(figsize=(18,5),dpi=200)
         sns.set_style('darkgrid')

         plt.subplot(121)
         plt.title('Model Accuracy/Loss',fontsize=15)
         plt.xlabel('Epochs',fontsize=12)
         plt.plot(error['loss'])
         plt.plot(error['accuracy'])

         plt.subplot(122)
         plt.title('Validation Accuracy/Loss',fontsize=15)
         plt.xlabel('Epochs',fontsize=12)
         plt.plot(error['val_loss'])
         plt.plot(error['val_accuracy'])

         plt.show()
```



Evaluation

```
In [18]: # Evaluate for train generator
         loss,acc = model.evaluate(train_generator,batch_size = bat_size, verbose = 0)

         print('The accuracy of the model for training data is:',acc*100)
         print('The Loss of the model for training data is:',loss)

         # Evaluvate for validation generator
         loss,acc = model.evaluate(test_generator,batch_size = bat_size, verbose = 0)

         print('The accuracy of the model for test data is:',acc*100)
         print('The Loss of the model for test data is:',loss)

         The accuracy of the model for training data is: 99.78500008583069
         The Loss of the model for training data is: 0.022451674565672874
         The accuracy of the model for test data is: 81.84000253677368
         The Loss of the model for test data is: 0.5144171118736267
```

```
In [19]: # Save the Model
         model.save("model.keras")
```

In [20]:
```
# prediction
result = model.predict(test_generator,batch_size = bat_size,verbose = 0)

y_pred = np.argmax(result, axis = 1)

y_true = test_generator.labels

# Evaluate
loss,acc = model.evaluate(test_generator, batch_size = bat_size, verbose = 0)

print('The accuracy of the model for testing data is:',acc*100)
print('The Loss of the model for testing data is:',loss)
```

```
The accuracy of the model for testing data is: 81.84000253677368
The Loss of the model for testing data is: 0.5144171118736267
```

In [21]:
```
labels =['Cat','Dog']
print(classification_report(y_true, y_pred,target_names=labels))
```

```
              precision    recall  f1-score   support

         Cat       0.80      0.86      0.82      2500
         Dog       0.84      0.78      0.81      2500

    accuracy                           0.82      5000
   macro avg       0.82      0.82      0.82      5000
weighted avg       0.82      0.82      0.82      5000
```

Batch Processing Predict

In [49]:
```
# Function to load and preprocess images
def preprocess_image(img_path, target_size=(128, 128)):
    img = image.load_img(img_path, target_size=target_size)
    img_array = image.img_to_array(img)
    img_array = np.expand_dims(img_array, axis=0)
    return img_array


import cv2
def pred_single(path):
    img = imread(path)

    rescaled_image = preprocess_image(img_path, target_size=(128, 128))

    rescaled_image /= 255.0
    # Make predictions
    predictions = model.predict(rescaled_image)

    # Assuming you have binary classification, extract the class with the highest probability
    predicted_class = np.argmax(predictions)

    if predicted_class == 0:
        pred = 'cat'
    else:
        pred='dog'

    return [img, pred]
```

In [50]:

```python
test = 'C:/Users/zhaox/Northwestern HW/CatDog/test'


imgs = []
preds = []

for index in [1, 10, 20, 50, 100, 500, 1000, 5000, 7500, 10000]:
    img_path = test + '/' + str(index) + '.jpg'

    output = pred_single(img_path)

    imgs.append(output[0])
    preds.append(output[1])


plt.figure(figsize=(10,10)) # specifying the overall grid size
plt.subplots_adjust(hspace=0.4)


for i in range(10):

    plt.subplot(2, 5,i+1)    # the number of images in the grid is 10*10 (100)
    plt.imshow(imgs[i])
    plt.title(f'{preds[i]}',fontsize=12)
    plt.axis('off')

plt.show()
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 16ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step
```

In [26]:
```
import os
import numpy as np
from tensorflow.keras.preprocessing import image

# Set up paths
test_data_dir = 'C:/Users/zhaox/Northwestern HW/CatDog/test'

# Load and preprocess test images
test_images = []
image_ids = []
for img_file in os.listdir(test_data_dir):
    img_path = os.path.join(test_data_dir, img_file)
    img_id = img_file.split('.')[0]  # Extract image ID from filename
    img = preprocess_image(img_path)
    test_images.append(img)
    image_ids.append(img_id)
test_images = np.vstack(test_images)

# Rescale the test images
test_images /= 255.0
```

In [37]:
```
# Predict probabilities for being a dog for each test image
probabilities = model.predict(test_images)

# Output image IDs and probabilities of being a dog
output = [(img_id, prob[1]) for img_id, prob in zip(image_ids, probabilities)]

# Print first few entries for demonstration
for img_id, prob_dog in output[:10]:
    print(f"Image ID: {img_id}, Probability of being a dog: {prob_dog}")
```

```
391/391 ━━━━━━━━━━━━━━━━━━━━ 9s 22ms/step
Image ID: 1, Probability of being a dog: 0.912966251373291
Image ID: 10, Probability of being a dog: 6.12250150879845e-05
Image ID: 100, Probability of being a dog: 0.5680259466171265
Image ID: 1000, Probability of being a dog: 0.999992847442627
Image ID: 10000, Probability of being a dog: 0.9997290968894958
Image ID: 10001, Probability of being a dog: 8.334402809850872e-05
Image ID: 10002, Probability of being a dog: 0.0003330996842123568
Image ID: 10003, Probability of being a dog: 0.8204399347305298
Image ID: 10004, Probability of being a dog: 0.015362096019089222
Image ID: 10005, Probability of being a dog: 0.00027356197824701667
```

In [44]:
```
upload = pd.DataFrame(output)
upload = upload.rename(columns={0:'id',1:'label'})
upload['id']=pd.to_numeric(upload['id'])
upload['label']=pd.to_numeric(upload['label'])
upload =upload.sort_values(by='id')
upload
```

Out[44]:

	id	label
0	1	9.129663e-01
3612	2	9.998078e-01
4723	3	9.842787e-01
5834	4	9.999989e-01
6945	5	7.657635e-07
...	...	...
2775	12496	2.558426e-07
2776	12497	3.956699e-02
2777	12498	9.638325e-01
2778	12499	9.999770e-01
2781	12500	2.303587e-10

12500 rows × 2 columns

In [45]:
```
upload.to_csv('CNN_2.csv',index=False)
```

Dogs vs. Cats Redux: Kernels Edition

Distinguish images of dogs from cats

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CNN_2.csv

Submitted by JZHAO8 · Submitted a day ago

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