Cats vs Dogs

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ABSTRACT:

This project focuses on classifying images into two categories: cats and dogs. We employ convolutional neural networks (CNNs) which are widely used for image classification. The dataset comprises images of cats and dogs, which are split into training and test sets. The model is trained on the training set and evaluated on the test set to assess its performance. The Model consists of various layers such as Convolution layer, Batch Normalization layer ,Dropout layer ,Dense layer with Relu(Rectified Linear Unit) activation function ,Adam optimizer, sigmoid function at output layer .Each Layer helps the model to become more robust. After the model achieves a high accuracy rate it is evaluated by making it predict from new dataset. Dataset is taken from Kaggle.

OBJECTIVE:

The objective of this project is to build a CNN model capable of accurately distinguishing between images of cats and dogs. By utilizing deep learning techniques along with required preprocessing, we aim to achieve a high level of classification accuracy on unseen data.

INTRODUCTION:

Image classification is a fundamental task in computer vision, with applications ranging from medical diagnosis to autonomous driving. In this project, we tackle the task of classifying images of cats and dogs using a CNN architecture. CNNs have proven to be highly effective in image classification tasks due to their ability to learn hierarchical features directly from raw pixel data.

This task holds practical significance in various domains, including pet identification, wildlife monitoring, and security surveillance. By accurately distinguishing between cats and dogs in images, we can automate tasks such as pet registration, animal counting in wildlife reserves, and identifying potential security threats .So let us dive deeper into neural network used in the project.

- 1. Convolutional Layers: (Feature Extraction)
 - Each layer applies a set of learnable filters (kernels) to the input image, performing convolution operations to extract various features such as edges, textures, and shapes.
- 2. **Pooling Layers**: (Reduce Dimension of input)
 - Common pooling operations include max pooling and average pooling, which help in reducing computational complexity, preventing overfitting, and increasing translation invariance.
- 3. Activation Functions: (Introduce non-linearity)
 - Activation functions enable CNNs to learn complex relationships and make non-linear predictions.

 Common activation functions include ReLU (Rectified Linear Unit), sigmoid, and tanh, which introduce non-linear transformations to the output of convolutional and fully connected layers.

4. Batch Normalization:

- Batch normalization is a technique used to stabilize and accelerate the training of deep neural networks.
- It normalizes the activations of each layer by adjusting and scaling them to have zero mean and unit variance, which helps in reducing internal covariate shift, improving gradient flow, and allowing for higher learning rates.

5. **Dropout Regularization**:

- Dropout regularization is a regularization technique used to prevent overfitting in deep neural networks.
- It randomly selects a subset of neurons in a layer and sets their outputs to zero during training, effectively dropping them out of the network. This forces the network to learn redundant representations and improves its generalization capability.

METHODOLOGY:

1. Data Preparation:

- The training and validation data are prepared using ImageDataGenerator from Keras. Data augmentation techniques such as rescaling, shearing, zooming, and horizontal flipping are applied to the training data to increase its diversity and improve the model's generalization.
- The training and validation data are loaded using **flow_from_directory** method, specifying the target size, batch size, and class mode.

2. Model Definition:

- The CNN model is defined using **Sequential** from TensorFlow/Keras.
- Convolutional layers with batch normalization, max pooling, and dropout are added to extract features from the input images.
- Flatten layer is used to flatten the 2D feature maps to 1D.
- Fully connected dense layers with batch normalization and dropout are added for classification.
- The output layer with sigmoid activation function is used for binary classification (cat or dog).

- The model is compiled with the Adam optimizer, binary crossentropy loss, and accuracy metric.
- Total number of layers in this model are 22+1 output layer.

3. Model Training:

- The model is trained using the **fit** method. Training data (**train_data**) and validation data (**validation_generator**) are passed as input.
- The training process runs for 30 epochs, and the model's performance is evaluated on the validation set after each epoch.

4. Prediction:

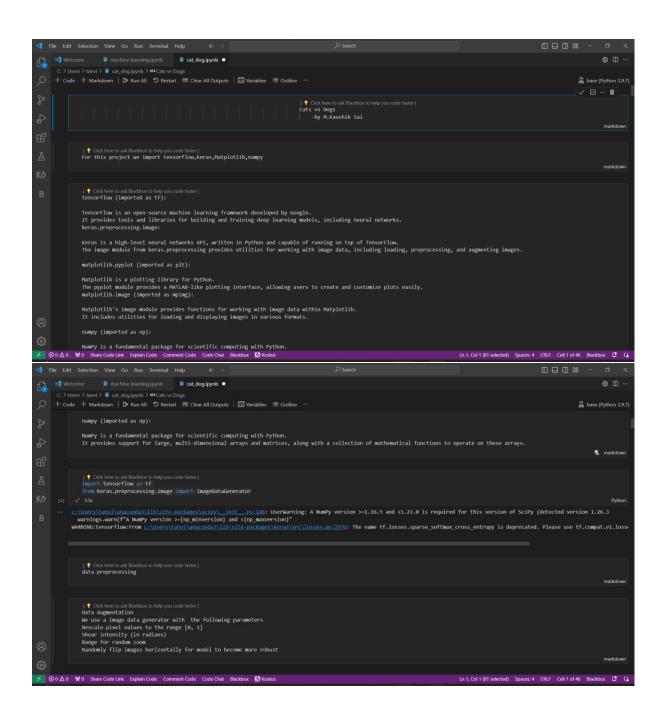
- After training, the model is used to make predictions on a set of test images (Pred1.jpg to Pred12.jpg).
- Each test image is loaded, pre-processed(resizing), and passed through the trained model to predict whether it belongs to the "cat" or "dog" class.
- The predictions are printed, and the corresponding images are displayed using matplotlib.

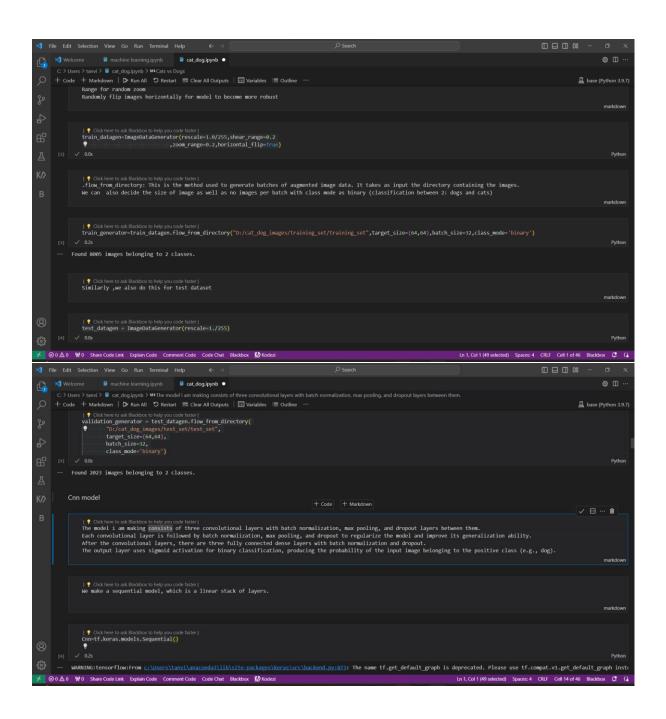
5. Visualization:

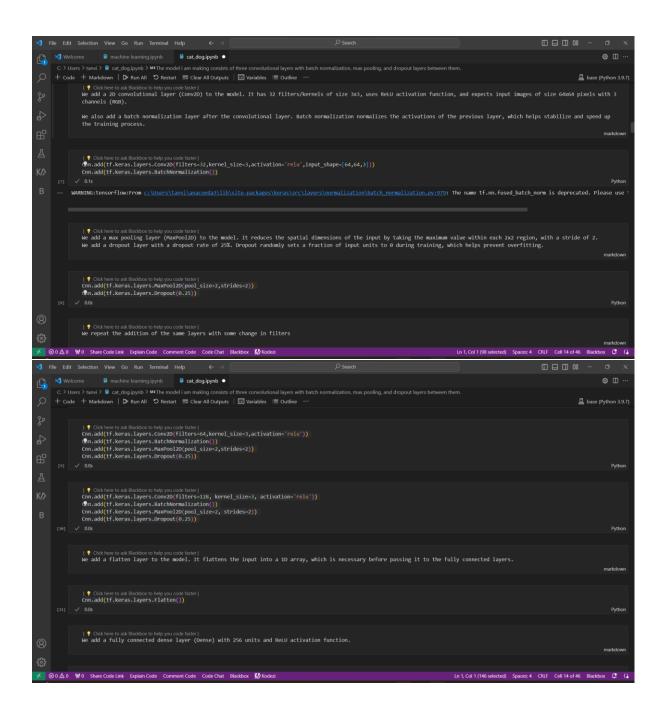
• Finally, the training history (accuracy and loss) is visualized using **matplotlib** to understand the training progress and model performance over epochs.

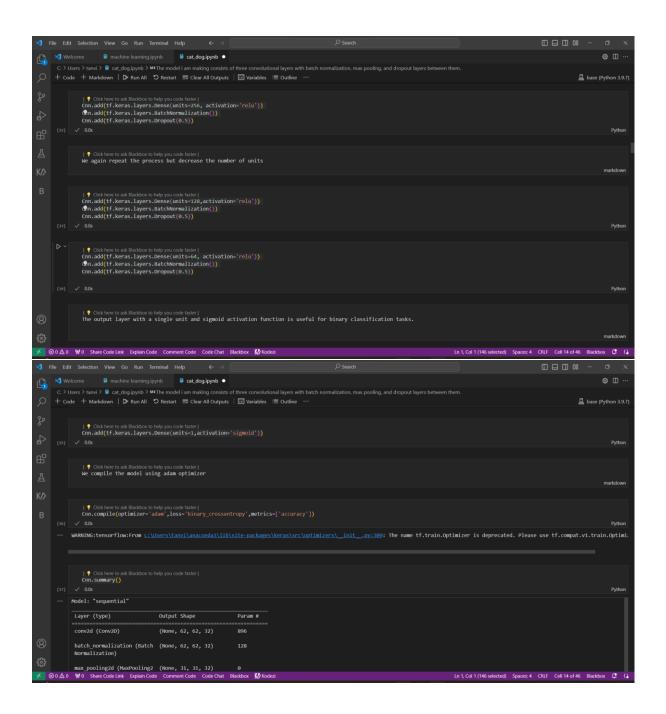
CODE:

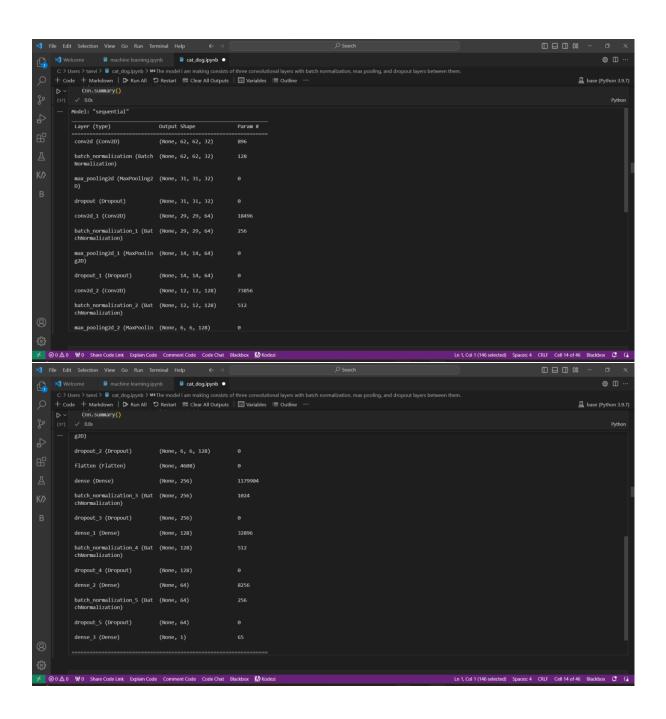
I have used jupyter notebook to explain each line. I have taken screenshots for the following outputs(code in text is present after screenshots)

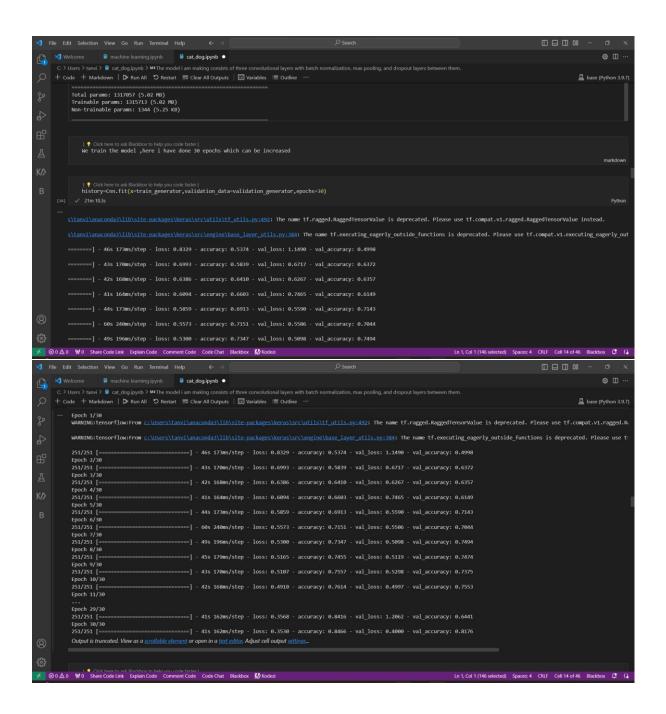


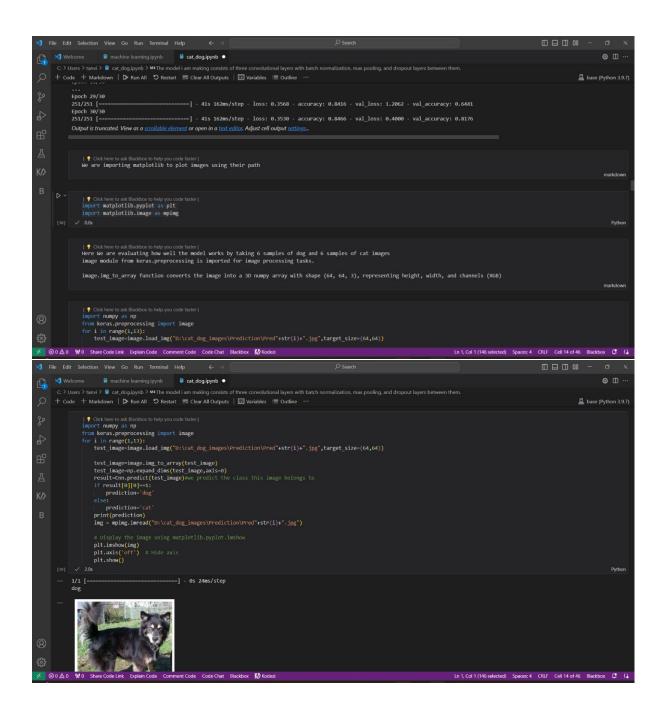


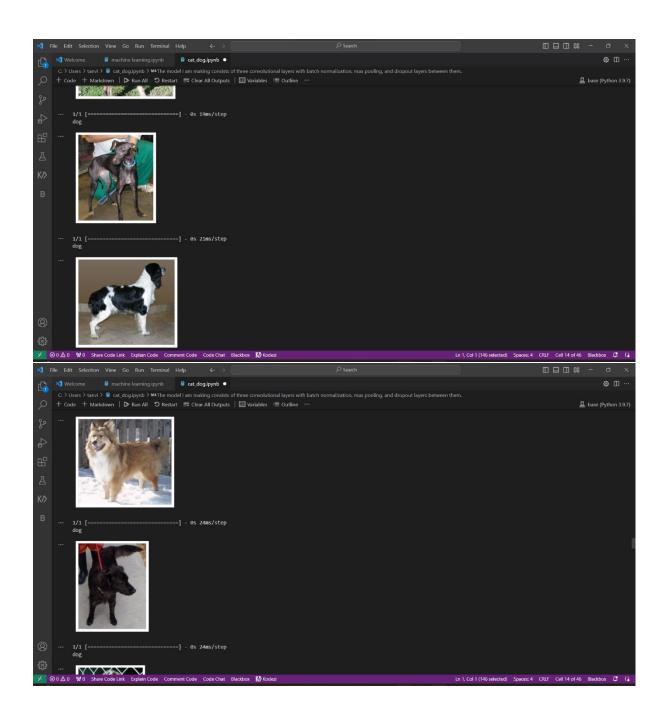


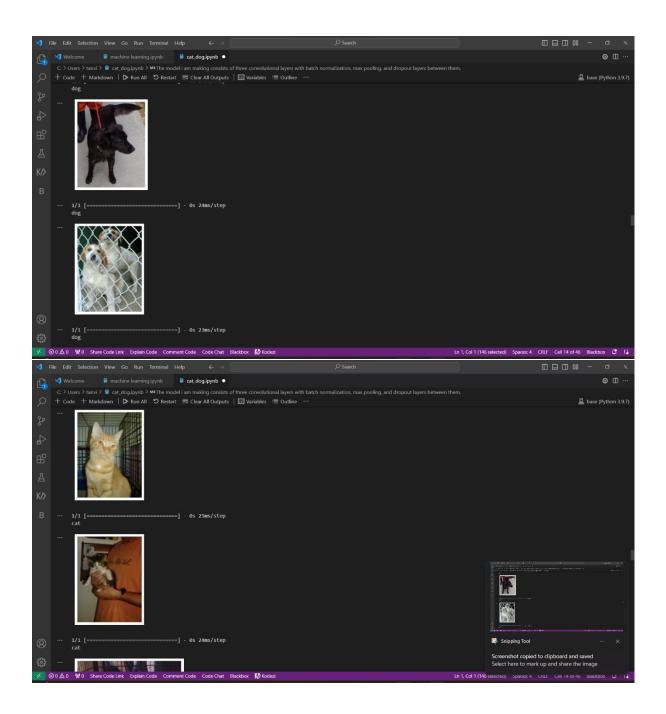


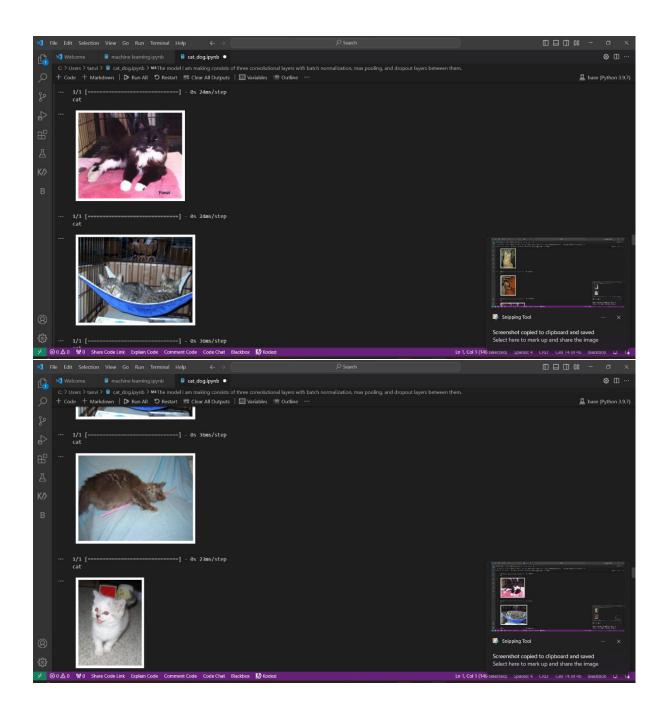


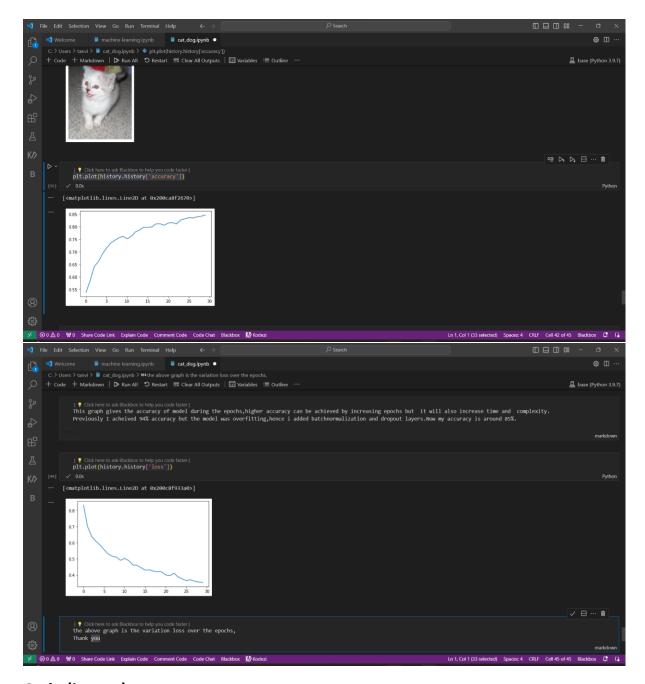












Code (in text):

import tensorflow as tf

from keras.preprocessing.image import ImageDataGenerator

train_gen=ImageDataGenerator(rescale=1.0/255,shear_range=0.2

,zoom_range=0.2,horizontal_flip=True)

train_data=train_gen.flow_from_directory("D:/cat_dog_images/training_set/training_set",target_siz e=(64,64),batch_size=32,class_mode='binary')

test_datagen = ImageDataGenerator(rescale=1./255)

validation_generator = test_datagen.flow_from_directory(

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"D:/cat_dog_images/test_set/test_set",
    target_size=(64,64),
    batch_size=32,
    class_mode='binary')
Cnn=tf.keras.models.Sequential()
Cnn.add(tf.keras.layers.Conv2D(filters=32,kernel size=3,activation='relu',input shape=[64,64,3]))
Cnn.add(tf.keras.layers.BatchNormalization())
Cnn.add(tf.keras.layers.MaxPool2D(pool_size=2,strides=2))
Cnn.add(tf.keras.layers.Dropout(0.25))
Cnn.add(tf.keras.layers.Conv2D(filters=64,kernel_size=3,activation='relu'))
Cnn.add(tf.keras.layers.BatchNormalization())
Cnn.add(tf.keras.layers.MaxPool2D(pool_size=2,strides=2))
Cnn.add(tf.keras.layers.Dropout(0.25))
Cnn.add(tf.keras.layers.Conv2D(filters=128, kernel_size=3, activation='relu'))
Cnn.add(tf.keras.layers.BatchNormalization())
Cnn.add(tf.keras.layers.MaxPool2D(pool_size=2, strides=2))
Cnn.add(tf.keras.layers.Dropout(0.25))
Cnn.add(tf.keras.layers.Flatten())
Cnn.add(tf.keras.layers.Dense(units=256, activation='relu'))
Cnn.add(tf.keras.layers.BatchNormalization())
Cnn.add(tf.keras.layers.Dropout(0.5))
Cnn.add(tf.keras.layers.Dense(units=128,activation='relu'))
Cnn.add(tf.keras.layers.BatchNormalization())
Cnn.add(tf.keras.layers.Dropout(0.5))
```

```
Cnn.add(tf.keras.layers.Dense(units=64, activation='relu'))
Cnn.add(tf.keras.layers.BatchNormalization())
Cnn.add(tf.keras.layers.Dropout(0.5))
Cnn.add(tf.keras.layers.Dense(units=1,activation='sigmoid'))
Cnn.compile(optimizer='adam',loss='binary_crossentropy',metrics=['accuracy'])
Cnn.summary()
history=Cnn.fit(x=train_data,validation_data=validation_generator,epochs=30)
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
import numpy as np
from keras.preprocessing import image
for i in range(1,13):
test_image=image.load_img("D:\cat_dog_images\Prediction\Pred"+str(i)+".jpg",target_size=(64,64))
  test_image=image.img_to_array(test_image)
  test_image=np.expand_dims(test_image,axis=0)
  result=Cnn.predict(test_image)#we predict the class this image belongs to
  if result[0][0]==1:
    prediction='dog'
  else:
    prediction='cat'
  print(prediction)
  img = mpimg.imread("D:\cat_dog_images\Prediction\Pred"+str(i)+".jpg")
  # Display the image using matplotlib.pyplot.imshow
```

```
plt.imshow(img)

plt.axis('off') # Hide axis

plt.show()

plt.plot(history.history['accuracy'])

plt.plot(history.history['loss'])
```

CONCLUSION:

We have successfully implemented a CNN model for classifying images of cats and dogs. The model demonstrates good performance, achieving high accuracy(85%,can increase but must take note of overfitting and optimal number of epochs, increasing amount of data for each class i.e cat and dog)on both the training and validation sets. Through this project, we have showcased the effectiveness of deep learning techniques, particularly CNNs, in image classification tasks. Further optimizations and fine-tuning could potentially enhance the model's performance for real-world applications.

The successful development of the CNN model for classifying cats and dogs has broader implications in various domains, including pet identification, wildlife monitoring, and security surveillance. The model can be deployed in real-world scenarios to automate tasks such as pet registration, animal counting, thereby enhancing operational efficiency and accuracy.