In [1]:
```
import tensorflow as tf
import random
import os
import numpy as np
from sklearn.metrics import roc_curve, auc, precision_recall_curve, average_precision_score, confusion_matrix
import pandas as pd
import matplotlib.pyplot as plt
from tensorflow.keras import models, layers
import seaborn as sns
```

Path system

In [2]:
```
# you need the current working directory NB: works both windows and linux
current_working_directory = os.getcwd()
current_working_directory = os.path.dirname(current_working_directory)

# get the directory where I want to download the dataset
path_of_download = os.path.join(current_working_directory, 'Part 2', 'Datasets', "cookies_vs_chihuahua")
print(f"[DIR] The directory of the current dataset is {path_of_download}")
```

```
[DIR] The directory of the current dataset is C:\UTU\2025\Computer Vision and Sensor Fusion\Part 2\Datasets\cookies_vs_chihuahu
a
```

Dataset function

In [3]:
```
# here let s do some functions that we can re-use also for other assignment
def load_the_data_and_the_labels(data_set_path: str, target_size: tuple or None = None):
    try:
        dataset, labels, name_of_the_labels = list(), list(), list()
        # let s loop here and we try to discover how many class we have
        for class_number, class_name in enumerate(os.listdir(data_set_path)):
            full_path_the_data = os.path.join(data_set_path, class_name)
            print(f"[WALK] I am walking into {full_path_the_data}")

            # add the list to nam _list
            name_of_the_labels.append(class_name)
```

```
            for single_image in os.listdir(f"{full_path_the_data}"):
                full_path_to_image = os.path.join(*[full_path_the_data, single_image])

                # add the class number
                labels.append(class_number)

                if target_size is None:
                    # let s load the image
                    image = tf.keras.utils.load_img(full_path_to_image)
                else:
                    image = tf.keras.utils.load_img(full_path_to_image, target_size=target_size)

                # transform PIL object in image
                image = tf.keras.utils.img_to_array(image)

                # add the image to the ds list
                dataset.append(image)

        return np.array(dataset, dtype='uint8'), np.array(labels, dtype='int'), name_of_the_labels
    except Exception as ex:
        print(f"[EXCEPTION] load the data and the labels throws exceptions {ex}")
        return None, None, None
```

In [4]:
```
def fix_image_shapes(dataset):
    # Check to make sure all images have dimensions (224, 224, 3)
    fixed_dataset = []
    for i, img in enumerate(dataset):
        if img.shape != (224, 224, 3):
            print(f"[WARNING] Image {i} has shape {img.shape}")
            img_pil = Image.fromarray(np.uint8(img * 255))  # Convert from NumPy -> PIL
            img_pil = img_pil.resize((224, 224))  # Resize Image
            img_fixed = np.array(img_pil) / 255.0  # Convert to NumPy array
            fixed_dataset.append(img_fixed)
        else:
            fixed_dataset.append(img)

    return np.array(fixed_dataset, dtype='float32')  # Convert to NumPy array
```

load train set

In [5]:
```
# Load train set
train_path = os.path.join(current_working_directory,'Part 2', 'Datasets', "cookies_vs_chihuahua", "train")
train_data, train_labels, train_classes = load_the_data_and_the_labels(train_path, target_size=(224, 224))
```

```
[WALK] I am walking into C:\UTU\2025\Computer Vision and Sensor Fusion\Part 2\Datasets\cookies_vs_chihuahua\train\chihuahua
[WALK] I am walking into C:\UTU\2025\Computer Vision and Sensor Fusion\Part 2\Datasets\cookies_vs_chihuahua\train\muffin
```

load test set

In [6]:
```
# Load test set
test_path = os.path.join(current_working_directory,'Part 2', 'Datasets', "cookies_vs_chihuahua", "test")
test_data, test_labels, test_classes = load_the_data_and_the_labels(test_path, target_size=(224, 224))
```

```
[WALK] I am walking into C:\UTU\2025\Computer Vision and Sensor Fusion\Part 2\Datasets\cookies_vs_chihuahua\test\chihuahua
[WALK] I am walking into C:\UTU\2025\Computer Vision and Sensor Fusion\Part 2\Datasets\cookies_vs_chihuahua\test\muffin
```

normalize the data

In [7]:
```
train_data = train_data / 255.0
test_data = test_data / 255.0
```

create a cnn with the following characteristics:

a. Input layer b. Data augmentation, with random flip and random rotation. c. Two hidden layers each composed with the following characteristics: 16 conv2d units, max pooling 2d and batch normalization, the second one should have 24 conv2d units max pooling 2d and batch normalization. d. After this, add a flatten layer and a dense layer with 8 units e. Add the final classifier (a dense layer) with the correct number of output and activation

In [8]:
```
# input shape
input_shape = (224, 224, 3)
num_classes = 2  # Binary classification

# build CNN model
model = models.Sequential([
    # Input Layer
    layers.Input(shape=input_shape),
```

```
    # data augmentation
    layers.RandomFlip("horizontal_and_vertical"),
    layers.RandomRotation(0.2),

    # first hidden Layer
    layers.Conv2D(16, (3, 3), activation='relu', padding='same'),
    layers.MaxPooling2D((2, 2), padding='same'),
    layers.BatchNormalization(),

    # second hidden Layer
    layers.Conv2D(24, (3, 3), activation='relu', padding='same'),
    layers.MaxPooling2D((2, 2), padding='same'),
    layers.BatchNormalization(),

    # Flatten Layer
    layers.Flatten(),
    layers.Dense(8, activation='relu'),
    layers.Dropout(0.3),  # add dropout to avoid overfitting

    # Output Layer
    layers.Dense(1, activation='sigmoid')  # 1 neuron for binary classification
])
```

compile the model using Adam

In [9]:

```
# Compile the model with Adam
model.compile(
    optimizer=tf.keras.optimizers.Adam(),  # Using Adam optimizer
    loss='sparse_categorical_crossentropy' if num_classes > 2 else 'binary_crossentropy',
    metrics=['accuracy']
)

# Model Summary
model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
random_flip (RandomFlip)	(None, 224, 224, 3)	0
random_rotation (RandomRotation)	(None, 224, 224, 3)	0
conv2d (Conv2D)	(None, 224, 224, 16)	448
max_pooling2d (MaxPooling2D)	(None, 112, 112, 16)	0
batch_normalization (BatchNormalization)	(None, 112, 112, 16)	64
conv2d_1 (Conv2D)	(None, 112, 112, 24)	3,480
max_pooling2d_1 (MaxPooling2D)	(None, 56, 56, 24)	0
batch_normalization_1 (BatchNormalization)	(None, 56, 56, 24)	96
flatten (Flatten)	(None, 75264)	0
dense (Dense)	(None, 8)	602,120
dropout (Dropout)	(None, 8)	0
dense_1 (Dense)	(None, 1)	9

Total params: 606,217 (2.31 MB)

Trainable params: 606,137 (2.31 MB)

Non-trainable params: 80 (320.00 B)

Train the model with batch size 64 and epochs of 30

In [10]:
```
# Train CNN model with batch size 64 and epochs of 30
history = model.fit(
    train_data, train_labels,
```

```
    epochs=30,
    batch_size=64,
    validation_data=(test_data, test_labels)
)
```

```
Epoch 1/30
74/74 ━━━━━━━━━━━━━━━━━━━━ 63s 749ms/step - accuracy: 0.6683 - loss: 1.0559 - val_accuracy: 0.4611 - val_loss: 3.6015
Epoch 2/30
74/74 ━━━━━━━━━━━━━━━━━━━━ 53s 705ms/step - accuracy: 0.7327 - loss: 0.5321 - val_accuracy: 0.4637 - val_loss: 5.3612
Epoch 3/30
74/74 ━━━━━━━━━━━━━━━━━━━━ 77s 642ms/step - accuracy: 0.7363 - loss: 0.5362 - val_accuracy: 0.5650 - val_loss: 0.9963
Epoch 4/30
74/74 ━━━━━━━━━━━━━━━━━━━━ 47s 631ms/step - accuracy: 0.7589 - loss: 0.4632 - val_accuracy: 0.5912 - val_loss: 1.0671
Epoch 5/30
74/74 ━━━━━━━━━━━━━━━━━━━━ 47s 639ms/step - accuracy: 0.7484 - loss: 0.4735 - val_accuracy: 0.5397 - val_loss: 1.2941
Epoch 6/30
74/74 ━━━━━━━━━━━━━━━━━━━━ 48s 648ms/step - accuracy: 0.7588 - loss: 0.4430 - val_accuracy: 0.5431 - val_loss: 0.9029
Epoch 7/30
74/74 ━━━━━━━━━━━━━━━━━━━━ 48s 647ms/step - accuracy: 0.7583 - loss: 0.4584 - val_accuracy: 0.5929 - val_loss: 0.6282
Epoch 8/30
74/74 ━━━━━━━━━━━━━━━━━━━━ 50s 680ms/step - accuracy: 0.7613 - loss: 0.4363 - val_accuracy: 0.7280 - val_loss: 0.5137
Epoch 9/30
74/74 ━━━━━━━━━━━━━━━━━━━━ 45s 601ms/step - accuracy: 0.7661 - loss: 0.4312 - val_accuracy: 0.8556 - val_loss: 0.3714
Epoch 10/30
74/74 ━━━━━━━━━━━━━━━━━━━━ 88s 687ms/step - accuracy: 0.7740 - loss: 0.4195 - val_accuracy: 0.7230 - val_loss: 0.6418
Epoch 11/30
74/74 ━━━━━━━━━━━━━━━━━━━━ 48s 647ms/step - accuracy: 0.7744 - loss: 0.4155 - val_accuracy: 0.6106 - val_loss: 0.5917
Epoch 12/30
74/74 ━━━━━━━━━━━━━━━━━━━━ 48s 651ms/step - accuracy: 0.7710 - loss: 0.4129 - val_accuracy: 0.8404 - val_loss: 0.3399
Epoch 13/30
74/74 ━━━━━━━━━━━━━━━━━━━━ 51s 689ms/step - accuracy: 0.7753 - loss: 0.4075 - val_accuracy: 0.8057 - val_loss: 0.4194
Epoch 14/30
74/74 ━━━━━━━━━━━━━━━━━━━━ 47s 629ms/step - accuracy: 0.7747 - loss: 0.4022 - val_accuracy: 0.7475 - val_loss: 0.5263
Epoch 15/30
74/74 ━━━━━━━━━━━━━━━━━━━━ 47s 630ms/step - accuracy: 0.7821 - loss: 0.4078 - val_accuracy: 0.8851 - val_loss: 0.2799
Epoch 16/30
74/74 ━━━━━━━━━━━━━━━━━━━━ 47s 633ms/step - accuracy: 0.7901 - loss: 0.3914 - val_accuracy: 0.8708 - val_loss: 0.3044
Epoch 17/30
74/74 ━━━━━━━━━━━━━━━━━━━━ 47s 630ms/step - accuracy: 0.7827 - loss: 0.3995 - val_accuracy: 0.8336 - val_loss: 0.3719
Epoch 18/30
74/74 ━━━━━━━━━━━━━━━━━━━━ 48s 641ms/step - accuracy: 0.7854 - loss: 0.3935 - val_accuracy: 0.8429 - val_loss: 0.3620
Epoch 19/30
74/74 ━━━━━━━━━━━━━━━━━━━━ 46s 620ms/step - accuracy: 0.7901 - loss: 0.4131 - val_accuracy: 0.7939 - val_loss: 0.5833
Epoch 20/30
74/74 ━━━━━━━━━━━━━━━━━━━━ 47s 627ms/step - accuracy: 0.7745 - loss: 0.4234 - val_accuracy: 0.8412 - val_loss: 0.3352
Epoch 21/30
```

```
74/74 ━━━━━━━━━━━━━━━━━━━━ 48s 648ms/step - accuracy: 0.7867 - loss: 0.3900 - val_accuracy: 0.7652 - val_loss: 0.4492
Epoch 22/30
74/74 ━━━━━━━━━━━━━━━━━━━━ 48s 651ms/step - accuracy: 0.7943 - loss: 0.3792 - val_accuracy: 0.7821 - val_loss: 0.4436
Epoch 23/30
74/74 ━━━━━━━━━━━━━━━━━━━━ 49s 663ms/step - accuracy: 0.7997 - loss: 0.3766 - val_accuracy: 0.7145 - val_loss: 0.5702
Epoch 24/30
74/74 ━━━━━━━━━━━━━━━━━━━━ 47s 632ms/step - accuracy: 0.7867 - loss: 0.3781 - val_accuracy: 0.7931 - val_loss: 0.4044
Epoch 25/30
74/74 ━━━━━━━━━━━━━━━━━━━━ 48s 645ms/step - accuracy: 0.7918 - loss: 0.3770 - val_accuracy: 0.7753 - val_loss: 0.4036
Epoch 26/30
74/74 ━━━━━━━━━━━━━━━━━━━━ 49s 661ms/step - accuracy: 0.7870 - loss: 0.3720 - val_accuracy: 0.8530 - val_loss: 0.3451
Epoch 27/30
74/74 ━━━━━━━━━━━━━━━━━━━━ 49s 663ms/step - accuracy: 0.7964 - loss: 0.3708 - val_accuracy: 0.8995 - val_loss: 0.2543
Epoch 28/30
74/74 ━━━━━━━━━━━━━━━━━━━━ 47s 628ms/step - accuracy: 0.7834 - loss: 0.3806 - val_accuracy: 0.7525 - val_loss: 0.4238
Epoch 29/30
74/74 ━━━━━━━━━━━━━━━━━━━━ 47s 636ms/step - accuracy: 0.8032 - loss: 0.3571 - val_accuracy: 0.8826 - val_loss: 0.3010
Epoch 30/30
74/74 ━━━━━━━━━━━━━━━━━━━━ 49s 657ms/step - accuracy: 0.7684 - loss: 0.3933 - val_accuracy: 0.7889 - val_loss: 0.4351
```

Evaluate the model and report the accuracy.

In [11]:

```python
# Evaluate on test set
test_loss, test_acc = model.evaluate(test_data, test_labels)
print(f"Accuracy: {test_acc:.4f}")
```

```
37/37 ━━━━━━━━━━━━━━━━━━━━ 3s 81ms/step - accuracy: 0.9179 - loss: 0.2157
Accuracy: 0.7889
```

Make prediction with the test set and use a threshold of 0.5 as boundaries decision between the classes.

In [12]:

```python
y_pred_prob = model.predict(test_data)
y_pred = (y_pred_prob > 0.5).astype(int)
y_true = test_labels.flatten()
print(f"Sample Predictions: {y_pred[:10].flatten()}")
print(f"True Labels: {y_true[:10]}")
```

```
37/37 ━━━━━━━━━━━━━━━━━━━━ 3s 75ms/step
Sample Predictions: [0 1 1 0 0 0 0 0 0 0]
True Labels: [0 0 0 0 0 0 0 0 0 0]
```

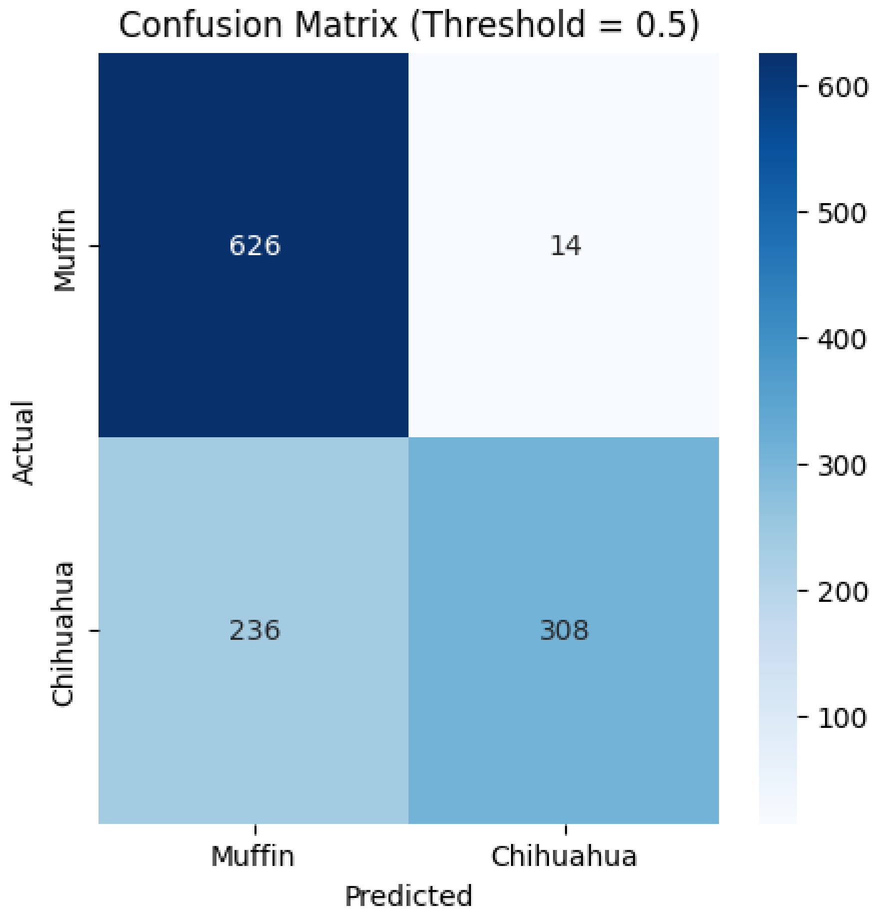
In [13]:
```
# Plot some predicted images
num_images = 5  # Show 5 images
plt.figure(figsize=(10, 5))

for i in range(num_images):
    plt.subplot(1, num_images, i+1)
    plt.imshow(test_data[i])
    plt.title(f"Pred: {y_pred[i][0]}")
    plt.axis("off")
plt.show()
```

plot confusion matrix and ROC curve

In [14]:
```
# Create confusion matrix based on y_true, y_pred
matrix = confusion_matrix(y_true, y_pred)

# Plot confusion matrix
plt.figure(figsize=(5, 5))
sns.heatmap(matrix, annot=True, fmt="d", cmap="Blues", xticklabels=["Muffin", "Chihuahua"], yticklabels=["Muffin", "Chihuahua"
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix (Threshold = 0.5)")
plt.show()
```



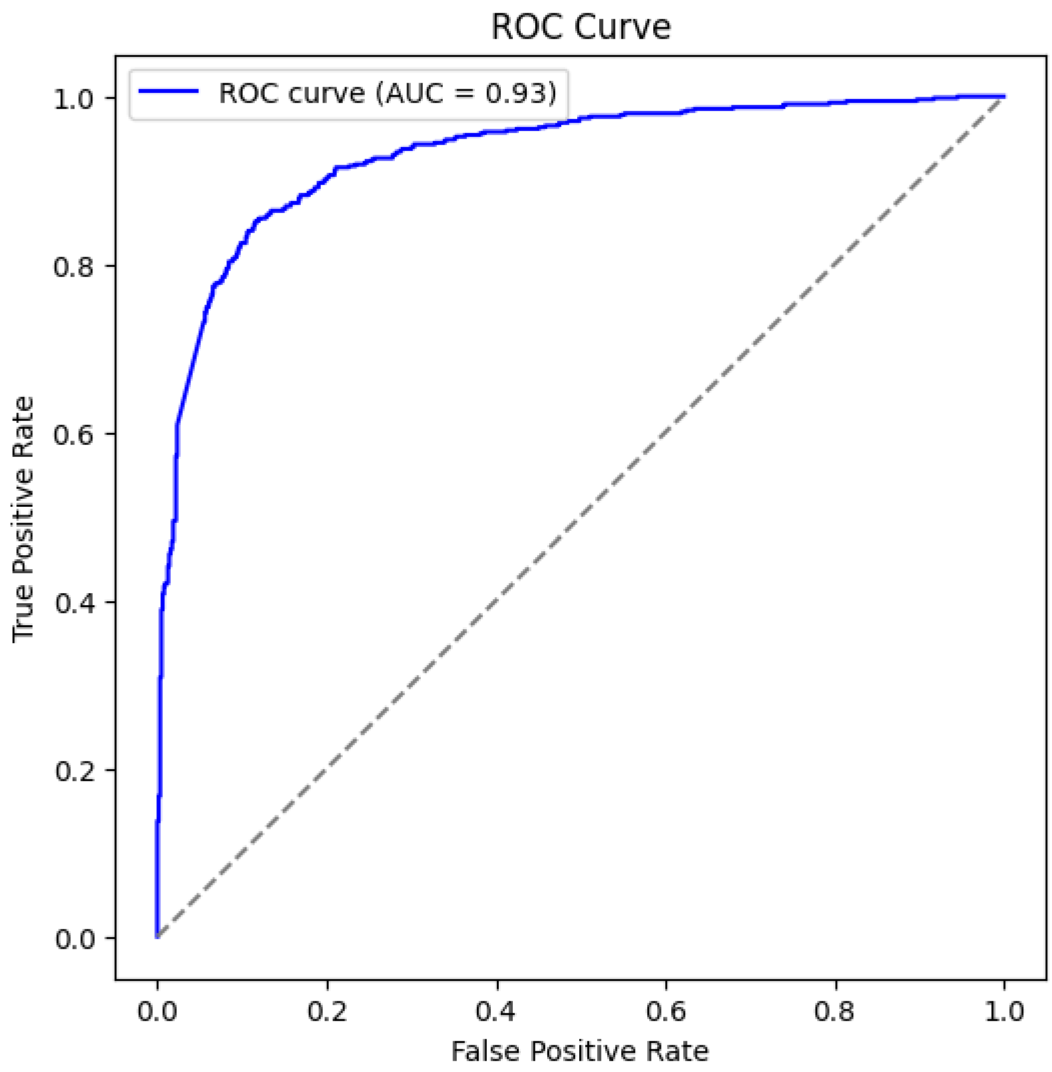
In [15]:

```
# Compute ROC curve
fpr, tpr, thresholds = roc_curve(y_true, y_pred_prob)

# Compute AUC
roc_auc = auc(fpr, tpr)

# Plot ROC curve
plt.figure(figsize=(6, 6))
plt.plot(fpr, tpr, color="blue", label=f"ROC curve (AUC = {roc_auc:.2f})")
plt.plot([0, 1], [0, 1], color="gray", linestyle="--")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
```

```
plt.title("ROC Curve")
plt.legend()
plt.show()
```



In [16]:
```
# Find the best Threshold np.argmax(tpr - fpr)
best_threshold_idx = np.argmax(tpr - fpr)
best_threshold = thresholds[best_threshold_idx]
```

```
print(f"Best Threshold: {best_threshold:.4f}")
```

```
Best Threshold: 0.2345
```

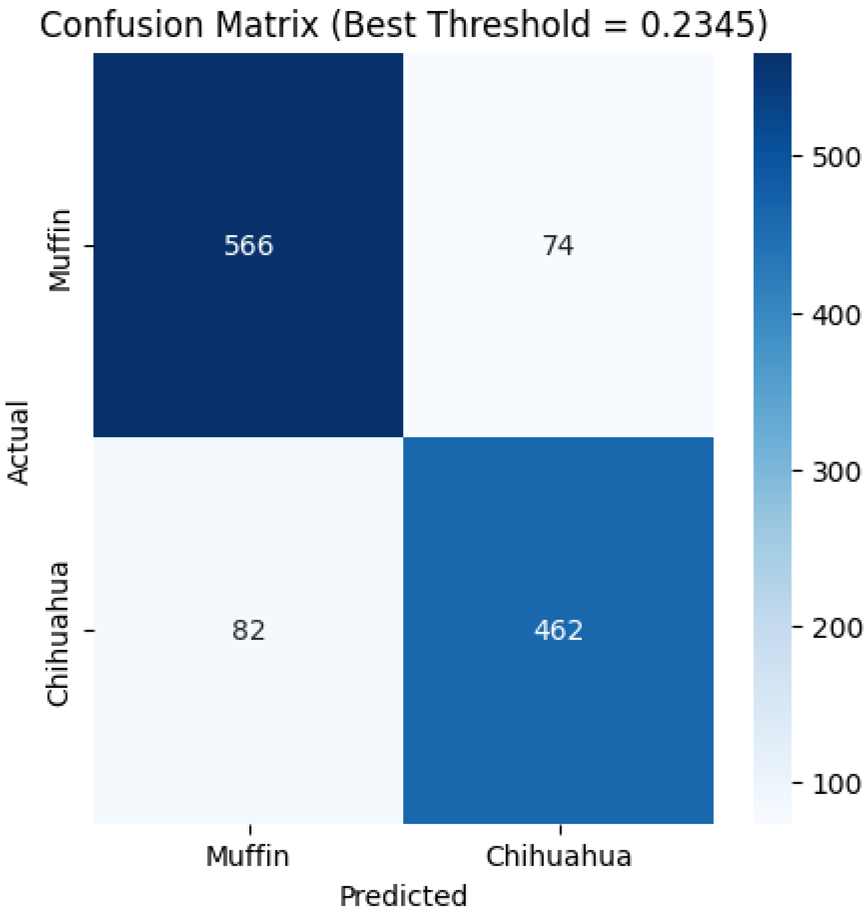
Calcualte best testhold

Plot confusion matrix

In [17]:
```
# Apply the best threshold
y_pred_best = (y_pred_prob > best_threshold).astype(int)

# Compute new confusion matrix
matrix = confusion_matrix(y_true, y_pred_best)

# Plot confusion matrix with best threshold
plt.figure(figsize=(5, 5))
sns.heatmap(matrix, annot=True, fmt="d", cmap="Blues", xticklabels=["Muffin", "Chihuahua"], yticklabels=["Muffin", "Chihuahua"
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title(f"Confusion Matrix (Best Threshold = {best_threshold:.4f})")
plt.show()
```



Confusion Matrix can give a clear picture of false positives, false negatives, and also true positives and true negatives. It helps to analyze the balance between precision and recall.

ROC curve shows how well the model separates positive and negative classes. It helps to find the best threesold rather using a fixed 0.5 thresold (AUC ~ 1.0 will give perfect classifier, and AUC ~ 0.5 will give radom guessing).