In [ ]:
```
# FLORIDA INTERNATIONAL UNIVERSITY (FIU)
# EEL6812 - ADVANCED TOPICS IN NEURAL NETWORKS (DEEP LEARNING)
# MOLTO, JOAQUIN (PID: 6119985)
# HW ASSIGNMENT #2 - CONVOLUTIONAL NEURAL NETWORKS
# DUE DATE: 04/10/2024
```

PVCM CLASSIFIERS (1=PANDA,0=NOT PANDA/CAT)

In [ ]:
```
# BRING NECESSARY FILES INTO THE SESSION
from google.colab import files
import os, shutil, pathlib
import tensorflow as tf
from tensorflow.keras.preprocessing import image_dataset_from_directory
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout
from tensorflow.keras.callbacks import ModelCheckpoint
from tensorflow.keras.regularizers import l1, l2
from tensorflow.keras import layers
import matplotlib.pyplot as plt
import numpy as np
```

In [ ]:
```
# INSTALL KAGGLE IF NOT ALREADY INSTALLED AND IMPORT KAGGLE.JSON INTO THE SESSION
!pip install kaggle
files.upload()
```

```
Requirement already satisfied: kaggle in /usr/local/lib/python3.10/dist-packages (1.
5.16)
Requirement already satisfied: six>=1.10 in /usr/local/lib/python3.10/dist-packages
(from kaggle) (1.16.0)
Requirement already satisfied: certifi in /usr/local/lib/python3.10/dist-packages (f
rom kaggle) (2024.2.2)
Requirement already satisfied: python-dateutil in /usr/local/lib/python3.10/dist-pac
kages (from kaggle) (2.8.2)
Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-packages
(from kaggle) (2.31.0)
Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-packages (from
kaggle) (4.66.2)
Requirement already satisfied: python-slugify in /usr/local/lib/python3.10/dist-pack
ages (from kaggle) (8.0.4)
Requirement already satisfied: urllib3 in /usr/local/lib/python3.10/dist-packages (f
rom kaggle) (2.0.7)
Requirement already satisfied: bleach in /usr/local/lib/python3.10/dist-packages (fr
om kaggle) (6.1.0)
Requirement already satisfied: webencodings in /usr/local/lib/python3.10/dist-packag
es (from bleach->kaggle) (0.5.1)
Requirement already satisfied: text-unidecode>=1.3 in /usr/local/lib/python3.10/dist
-packages (from python-slugify->kaggle) (1.3)
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.1
0/dist-packages (from requests->kaggle) (3.3.2)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packag
es (from requests->kaggle) (3.6)
```

Choose Files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving kaggle.json to kaggle.json
```

Out[ ]:
```
{'kaggle.json': b'{"username":"joaquinmolto","key":"d560844e63fba9ee27160fbc32ee7f
50"}'}
```

In [ ]:
```
# CREATES THE KAGGLE DIRECTORY IN THE SESSION, COPIES JSON FILE OVER, GRANTS PERMIS
!mkdir -p ~/.kaggle
!cp kaggle.json ~/.kaggle/
!chmod 600 ~/.kaggle/kaggle.json
```

In [ ]:
```
# USE KAGGLE CLI TO DOWNLOAD THE DATASET
!kaggle datasets download -d ashishsaxena2209/animal-image-datasetdog-cat-and-panda
```

```
Downloading animal-image-datasetdog-cat-and-panda.zip to /content
100% 375M/376M [00:17<00:00, 24.1MB/s]
100% 376M/376M [00:17<00:00, 21.9MB/s]
```

In [ ]:
```
!unzip -qq animal-image-datasetdog-cat-and-panda.zip
```

PART I. INITIAL REORGANIZATION OF THE DATA

- TRAIN **[TR]** = 700 patterns/samples each
- VALIDATION **[TT]** = 700 pattern/sample each
- TESTING **[TS]** = 700 pattern/sample each

Acknowledgement to Dr. Barreto for this portion of the Jupyter Notebook, as his code facilitated the creation of the subdirectories with the split data

In [ ]:
```
# DR. BARRETO'S DATA PREPARATION CODE
original_dir = pathlib.Path('animals')
new_base_dir = pathlib.Path('newanim')
def make_subset(subset_name, start_index, end_index):
  for category in ('cats', 'dogs', 'panda'):
    dir = new_base_dir / subset_name / category
    dirsrc = original_dir / category
    os.makedirs(dir)
    fnames = ['{}_{:05d}.jpg'.format(category, i)
                  for i in range(start_index, end_index)]
    for fname in fnames:
     shutil.copyfile(src=dirsrc / fname , dst=dir / fname)

    #print(fnames)
    #print(dirsrc)
    #print(dir)
# make_subset('train', start_index=0, end_index=1000)
# make_subset('validation', start_index=1000, end_index=1500)
# # make_subset('test', start_index=1500, end_index=2500)

make_subset('train', start_index=1, end_index=701) # will grab first 700 .jpeg file
make_subset('validation', start_index=701, end_index=901) # will grab remaining 200
make_subset('test', start_index=901, end_index=1001) # will grab last 100 .jpeg fil
```

In [ ]:
```
# verify the 3 subdirectories were created
!ls -l ./newanim/
```

```
total 12
drwxr-xr-x 5 root root 4096 Apr 11 03:56 test
drwxr-xr-x 5 root root 4096 Apr 11 03:56 train
drwxr-xr-x 5 root root 4096 Apr 11 03:56 validation
```

PART II. DOGS VERSUS PANDAS CLASSIFIER

Before we start building the Convolutional Neural Network (CNN) and the Fully-Connected or Dense Neural Network, we must remove the cat subdirectories for TR, TT, TS folders

In [ ]:
```
# REMOVE ALL 3 DOG SUBDIRECTORIES FROM THE TRAINING, VALIDATION, AND TESTING FOLDER
!rm -r ./newanim/train/dogs/
!rm -r ./newanim/validation/dogs/
!rm -r ./newanim/test/dogs/
```

In [ ]:
```
# ENSURE THE DOG SUBDIRECTORY IS GONE FROM THESE THREE SUBDIRECTORIES
!dir ./newanim/train
!dir ./newanim/validation
!dir ./newanim/test
```

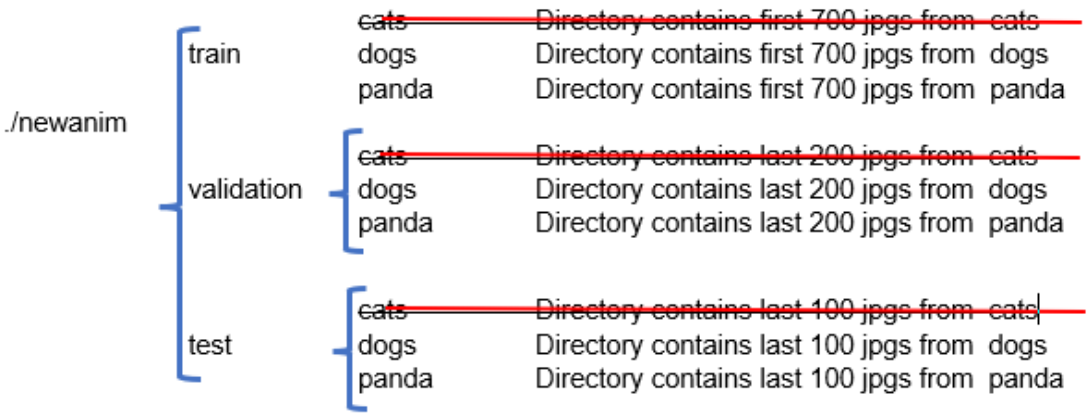
```
cats  panda
cats  panda
cats  panda
```

In [ ]:
```
# NOW, WE HAVE CREATE THE TF (TENSORFLOW) DATASET
train_dataset = image_dataset_from_directory(
        new_base_dir / 'train',
```

```
        image_size=(180, 180),
        batch_size=32)
validation_dataset = image_dataset_from_directory(
        new_base_dir / 'validation',
        image_size=(180, 180),
        batch_size=32)
test_dataset = image_dataset_from_directory(
        new_base_dir / 'test',
        image_size=(180, 180),
        batch_size=32)
```

```
Found 1400 files belonging to 2 classes.
Found 400 files belonging to 2 classes.
Found 200 files belonging to 2 classes.
```

Therefore, our directory structure now looks like this:



PART II.1 DOGS VERSUS PANDAS CLASSIFIER (pvcm1)

Develop a first, relatively simple CNN model named pvcm1 to classify Dogs versus Pandas

RESTRICTIONS:

1. CANNOT USE DROPOUT
2. CANNOT USE L1 OR L2 NORM PARAMETER REGULARIZATION
3. CANNOT USE DATA AUGMENTATION

pvcm1 Architecture:

- 2D Convolutional Neural Network (CNN)

** 3x3 Kernels/Filters (32 of them) ** MaxPool 2D Layer (size 2)

- 2D Convolutional Neural Network (CNN)

** 3x3 Kernels/Filters (32 of them) ** MaxPool 2D Layer (size 2)

- 2D Convolutional Neural Network (CNN)

** 3x3 Kernels/Filters (32 of them) ** MaxPool 2D Layer (size 2)

- Flattening Layer (Rank-1 Tensor)
- Fully-Connected/Dense Network (DNN)

** HL01: 128 PE with ReLU activation ** OL: 1 PE with Sigmoid activation

In [ ]:
```
# PREPROCESS THE IMAGES TO HAVE CONSISTENT DIMENSIONS AND PERFORM PIXEL NORMALIZATI

# while the instructions impede the use of neuron dropout, L1/L2 weight regularizat
# I will perform pixel-wise normalization by dividing by 255

# IMAGE PREPROCESSING FUNCTION
def normalize_image(image,label):
  return image / 255, label

# APPLY THE PREPROCESSING FUCTION TO THE TF DATASET
train_dataset = train_dataset.map(normalize_image)
validation_dataset = validation_dataset.map(normalize_image)
test_dataset = test_dataset.map(normalize_image)
```

In [ ]:
```
# DEFINE MODEL ARCHITECTURE FOR pvcm01 USING KERAS SEQUENTIAL API
pvcm1 = Sequential([
    Conv2D(32, (3, 3), activation='relu', input_shape=(180, 180, 3)),
    MaxPooling2D((2, 2)),
    Conv2D(64, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Conv2D(128, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Flatten(),
    Dense(128, activation='relu'),
    Dense(1, activation='sigmoid')
])
```

In [ ]:
```
# COMPILE THE MODEL
pvcm1.compile(optimizer='adam',
              loss='binary_crossentropy',
              metrics=['accuracy'])
```

In [ ]:
```
# SET UP CALLBACK SO THAT WE CAN RETURN THE MODEL (.KERAS) FILE WHOSE WEIGHTS ACHIE

# SPECIFY THE PATH TO SAVE THE BEST MODEL
model_save_path = "best_model.keras"

# SET UP THE MODEL_CHECKPOINT_CALLBACK MONITORING THE VAL_LOSS
model_checkpoint_callback = ModelCheckpoint(
    filepath=model_save_path,
    save_best_only=True,
    monitor='val_loss',
    mode='min',
    verbose=1
)
```

In [ ]:
```
# FIT THE MODEL
history = pvcm1.fit(train_dataset,
                    epochs=50,
                    validation_data=validation_dataset,
                    callbacks=[model_checkpoint_callback])
```

In [ ]:
```
# PRINT THE MODEL SUMMARY
pvcm1.summary()
```

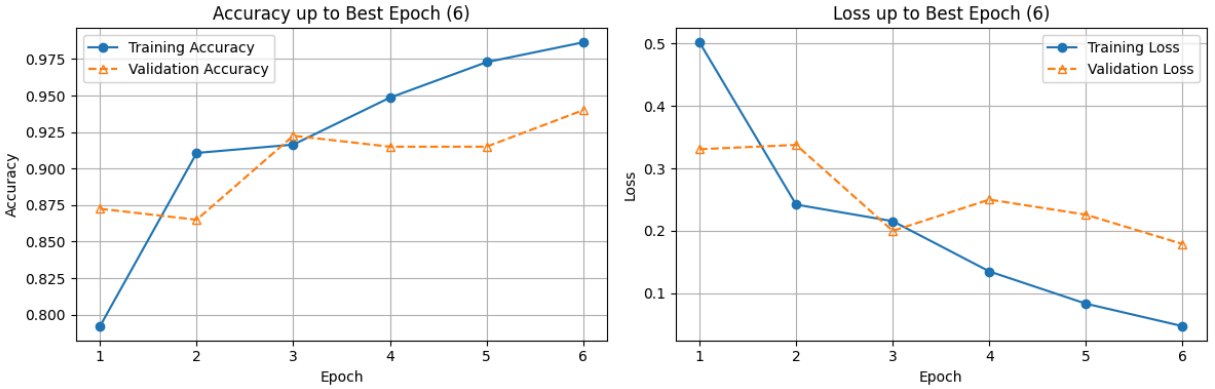
```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 178, 178, 32)      896

 max_pooling2d (MaxPooling2  (None, 89, 89, 32)        0
 D)

 conv2d_1 (Conv2D)           (None, 87, 87, 64)        18496

 max_pooling2d_1 (MaxPoolin  (None, 43, 43, 64)        0
 g2D)

 conv2d_2 (Conv2D)           (None, 41, 41, 128)       73856

 max_pooling2d_2 (MaxPoolin  (None, 20, 20, 128)       0
 g2D)

 flatten (Flatten)           (None, 51200)             0

 dense (Dense)               (None, 128)               6553728

 dense_1 (Dense)             (None, 1)                 129

=================================================================
Total params: 6647105 (25.36 MB)
Trainable params: 6647105 (25.36 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

In [ ]:
```
# EVALUATE THE MODEL
test_loss, test_accuracy = pvcm1.evaluate(test_dataset)
print(f'Test Loss: {test_loss}')
print(f'Test Accuracy: {test_accuracy}')
```

```
7/7 [==============================] - 0s 23ms/step - loss: 0.6283 - accuracy: 0.935
0
Test Loss: 0.6283135414123535
Test Accuracy: 0.9350000023841858
```

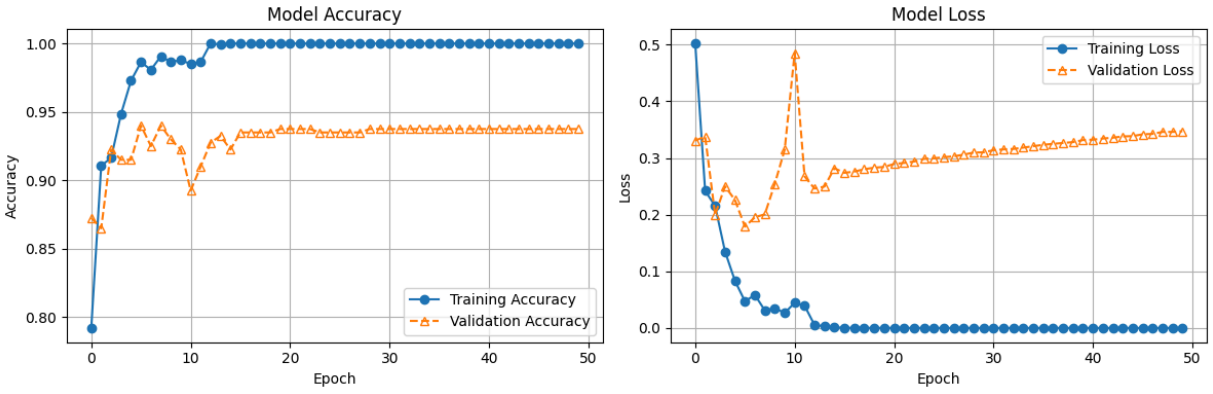
In [ ]:
```
def plot_history_until_best_epoch_modified(history):
    # Find the epoch number where the validation loss was minimum; epochs are 1-ind
    min_val_loss_epoch = history.history['val_loss'].index(min(history.history['val

    # Prepare the range for plotting
    epochs_range = range(1, min_val_loss_epoch + 1)
```

```
    plt.figure(figsize=(12, 4))

    # Plot Accuracy with markers and grid
    plt.subplot(1, 2, 1)
    plt.plot(epochs_range, history.history['accuracy'][:min_val_loss_epoch], 'o-',
    plt.plot(epochs_range, history.history['val_accuracy'][:min_val_loss_epoch], ma
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.title(f'Accuracy up to Best Epoch ({min_val_loss_epoch})')
    plt.legend()
    plt.grid(True)  # Display gridlines

    # Plot Loss with markers and grid
    plt.subplot(1, 2, 2)
    plt.plot(epochs_range, history.history['loss'][:min_val_loss_epoch], 'o-', labe
    plt.plot(epochs_range, history.history['val_loss'][:min_val_loss_epoch], marker
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.title(f'Loss up to Best Epoch ({min_val_loss_epoch})')
    plt.legend()
    plt.grid(True)  # Display gridlines

    plt.tight_layout()
    plt.show()

# Call the function with the history variable
plot_history_until_best_epoch_modified(history)
```



In [ ]:
```
# PLOT THE TRAINING AND VALIDATION CURVES

# Prepare the figure
plt.figure(figsize=(12, 4))

# Plot Training and Validation Accuracy
plt.subplot(1, 2, 1)  # 1 row, 2 columns, 1st subplot
plt.plot(history.history['accuracy'], 'o-', label='Training Accuracy')  # Circle ma
plt.plot(history.history['val_accuracy'], '^', linestyle='--', fillstyle='none', la
plt.title('Model Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend(loc='lower right')
plt.grid(True)  # Display gridlines
```

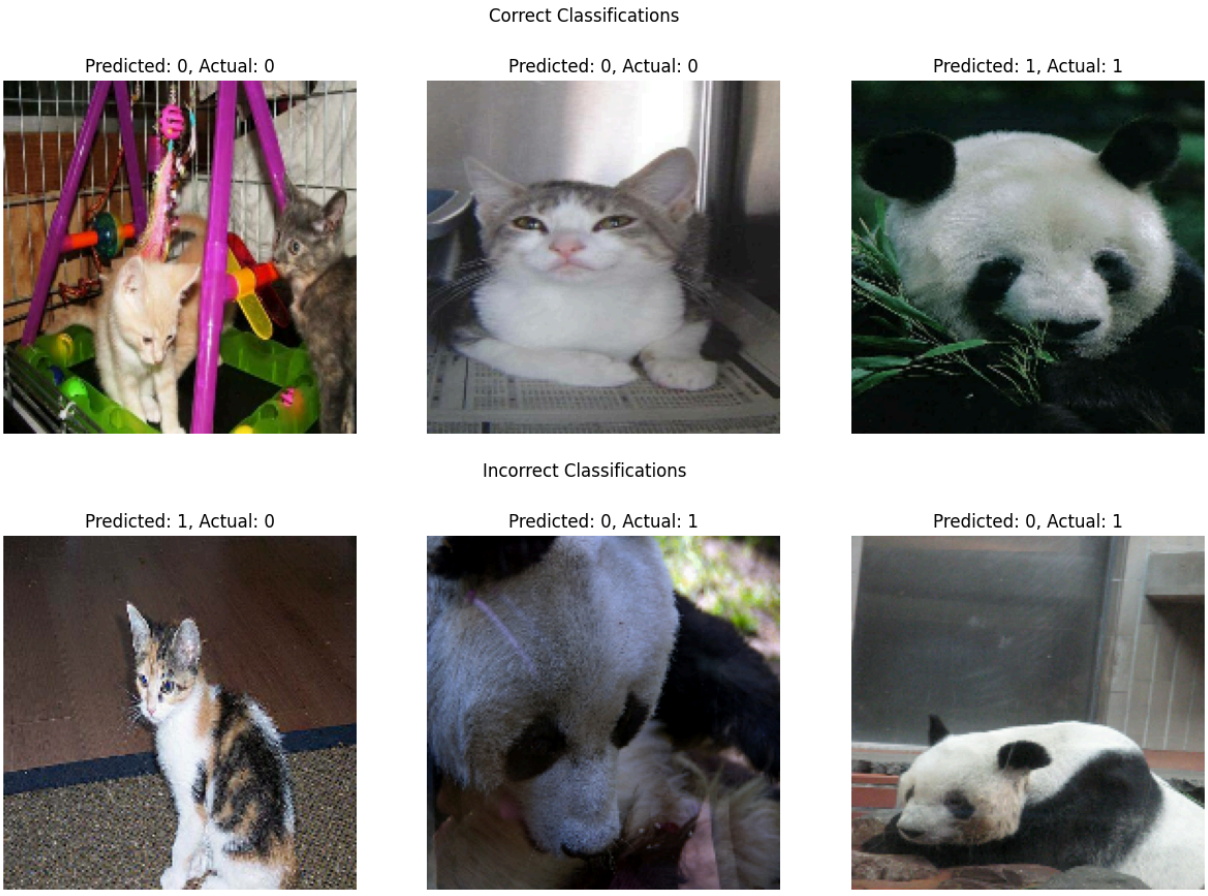
```
# Plot Training and Validation Loss
plt.subplot(1, 2, 2)  # 1 row, 2 columns, 2nd subplot
plt.plot(history.history['loss'], 'o-', label='Training Loss')  # Circle markers, s
plt.plot(history.history['val_loss'], marker='^', linestyle='--', fillstyle='none',
plt.title('Model Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend(loc='upper right')
plt.grid(True)  # Display gridlines

# Display the plots
plt.tight_layout()
plt.show()
```



In [ ]:
```
# Assuming test_dataset is batched: (image, label)
predictions = []
labels = []
images = []
for img, label in test_dataset.take(10):  # Adjust the number of batches to suit yo
    pred = pvcm1.predict(img)
    pred = np.round(pred).astype(int).flatten()  # Round predictions to 0 or 1 for
    predictions.extend(pred)
    labels.extend(label.numpy())
    images.extend(img.numpy())

# Convert lists to arrays for easier manipulation
predictions = np.array(predictions)
labels = np.array(labels)
images = np.array(images)

# Find indices of correct and incorrect predictions
correct_indices = np.where(predictions == labels)[0]
incorrect_indices = np.where(predictions != labels)[0]

# Function to plot images
def plot_images(indices, title):
    plt.figure(figsize=(15, 5))
    for i, idx in enumerate(indices[:3], start=1):  # Plot up to 3 images
        plt.subplot(1, 3, i)
        # Rescale the images back to 0-255 and convert to integers for display
        image_to_display = (images[idx] * 255).astype("uint8")
        plt.imshow(image_to_display)
```

```
        plt.title(f"Predicted: {predictions[idx]}, Actual: {labels[idx]}")
        plt.axis("off")
    plt.suptitle(title)
    plt.show()


# Plot correct classifications
plot_images(correct_indices, "Correct Classifications")

# Plot incorrect classifications
plot_images(incorrect_indices, "Incorrect Classifications")
```

```
1/1 [==============================] - 0s 110ms/step
1/1 [==============================] - 0s 23ms/step
1/1 [==============================] - 0s 23ms/step
1/1 [==============================] - 0s 23ms/step
1/1 [==============================] - 0s 23ms/step
1/1 [==============================] - 0s 23ms/step
1/1 [==============================] - 0s 77ms/step
```



PART II.2 DOGS VERSUS PANDAS CLASSIFIER (pvcm2)

Develop a second, further improved CNN

RESTRICTIONS:

1. CAN USE DROPOUT (OK)
2. CAN USE L1 OR L2 NORM PARAMETER REGULARIZATION (OK)
3. CANNOT USE DATA AUGMENTATION (NOT OK)

pvcm2 Architecture:

- 2D Convolutional Neural Network (CNN)

** L2 (Ridge) Regularizer of 1×10^-3 ** 3x3 Kernels/Filters (32 of them) ** MaxPool 2D Layer (size 2) ** Dropout Layer of 0.25 (25%)

- 2D Convolutional Neural Network (CNN)

** L2 (Ridge) Regularizer of 1×10^-3 ** 3x3 Kernels/Filters (32 of them) ** MaxPool 2D Layer (size 2) ** Dropout Layer of 0.25 (25%)

- 2D Convolutional Neural Network (CNN)

** L2 (Ridge) Regularizer of 1×10^-3 ** 3x3 Kernels/Filters (32 of them) ** MaxPool 2D Layer (size 2) ** Dropout Layer of 0.25 (25%)

- Flattening Layer (Rank-1 Tensor)
- Dropout Layer of 0.50 (50%)
- Fully-Connected/Dense Network (DNN)

** HL01: 128 PE with ReLU activation ** OL: 1 PE with Sigmoid activation

In [ ]:
```
# DEFINE MODEL ARCHITECTURE FOR pvcm02 USING KERAS SEQUENTIAL API
pvcm2 = Sequential([
    Conv2D(32, (3, 3), activation='relu', kernel_regularizer=l2(1E-3), input_shape=
    MaxPooling2D((2, 2)),
    Dropout(0.25), # dropout of 25% after first pooling
    Conv2D(64, (3, 3), activation='relu', kernel_regularizer=l2(1E-3)),
    MaxPooling2D((2, 2)),
    Dropout(0.25), # dropout of 25% after second pooling
    Conv2D(128, (3, 3), activation='relu', kernel_regularizer=l2(1E-3)),
    MaxPooling2D((2, 2)),
    Dropout(0.25), # dropout of 25% after third pooling
    Flatten(),
    Dense(128, activation='relu', kernel_regularizer=l2(1E-3)),
    Dropout(0.5), # dropout of 50% before output
    Dense(1, activation='sigmoid')
])
```

In [ ]:
```
# COMPILE THE MODEL
pvcm2.compile(optimizer='adam',
              loss='binary_crossentropy',
              metrics=['accuracy'])
```

In [ ]:
```
# SET UP CALLBACK SO THAT WE CAN RETURN THE MODEL (.KERAS) FILE WHOSE WEIGHTS ACHIE

# SPECIFY THE PATH TO SAVE THE BEST MODEL
model_save_path = "best_model.keras"

# SET UP THE MODEL_CHECKPOINT_CALLBACK MONITORING THE VAL_LOSS
```

```
model_checkpoint_callback = ModelCheckpoint(
    filepath=model_save_path,
    save_best_only=True,
    monitor='val_loss',
    mode='min',
    verbose=1
)
```

In [ ]:
```
# FIT THE MODEL
history = pvcm2.fit(train_dataset,
                    epochs=50,
                    validation_data=validation_dataset,
                    callbacks=[model_checkpoint_callback])
```

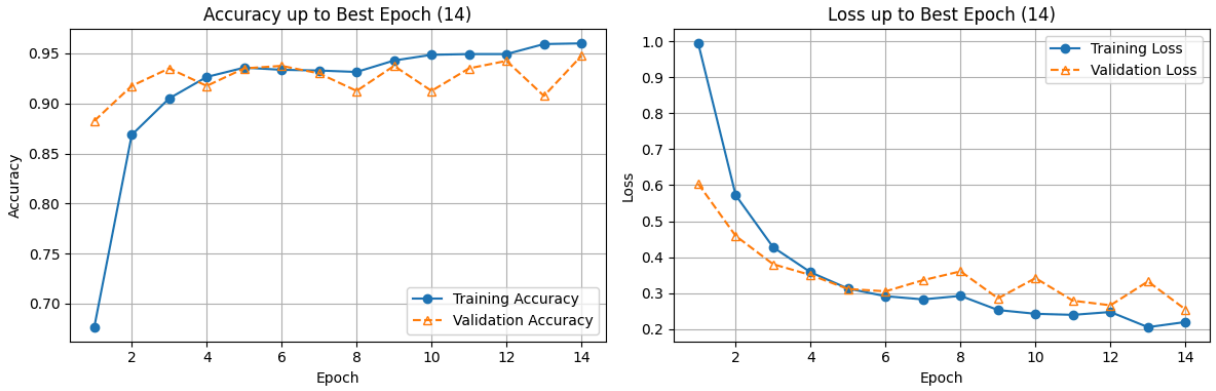
In [ ]:
```
# PRINT THE MODEL SUMMARY
pvcm2.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_3 (Conv2D)           (None, 178, 178, 32)      896

 max_pooling2d_3 (MaxPoolin  (None, 89, 89, 32)        0
 g2D)

 dropout (Dropout)           (None, 89, 89, 32)        0

 conv2d_4 (Conv2D)           (None, 87, 87, 64)        18496

 max_pooling2d_4 (MaxPoolin  (None, 43, 43, 64)        0
 g2D)

 dropout_1 (Dropout)         (None, 43, 43, 64)        0

 conv2d_5 (Conv2D)           (None, 41, 41, 128)       73856

 max_pooling2d_5 (MaxPoolin  (None, 20, 20, 128)       0
 g2D)

 dropout_2 (Dropout)         (None, 20, 20, 128)       0

 flatten_1 (Flatten)         (None, 51200)             0

 dense_2 (Dense)             (None, 128)               6553728

 dropout_3 (Dropout)         (None, 128)               0

 dense_3 (Dense)             (None, 1)                 129

=================================================================
Total params: 6647105 (25.36 MB)
Trainable params: 6647105 (25.36 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

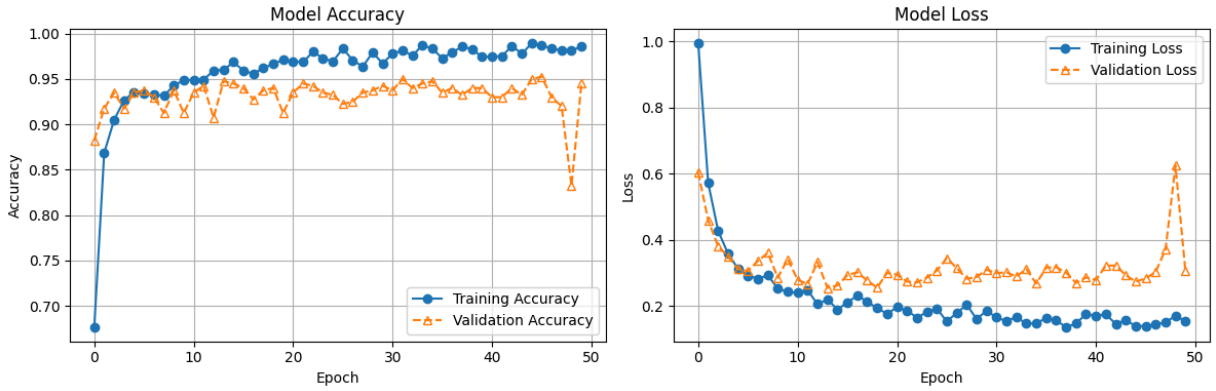
In [ ]:
```
# EVALUATE THE MODEL
test_loss, test_accuracy = pvcm2.evaluate(test_dataset)
print(f'Test Loss: {test_loss}')
print(f'Test Accuracy: {test_accuracy}')
```

```
7/7 [==============================] - 0s 6ms/step - loss: 0.3571 - accuracy: 0.9350
Test Loss: 0.3571350872516632
Test Accuracy: 0.9350000023841858
```

In [ ]:
```
def plot_history_until_best_epoch_modified(history):
    # Find the epoch number where the validation loss was minimum; epochs are 1-ind
    min_val_loss_epoch = history.history['val_loss'].index(min(history.history['val

    # Prepare the range for plotting
    epochs_range = range(1, min_val_loss_epoch + 1)

    plt.figure(figsize=(12, 4))

    # Plot Accuracy with markers and grid
    plt.subplot(1, 2, 1)
    plt.plot(epochs_range, history.history['accuracy'][:min_val_loss_epoch], 'o-',
    plt.plot(epochs_range, history.history['val_accuracy'][:min_val_loss_epoch], ma
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.title(f'Accuracy up to Best Epoch ({min_val_loss_epoch})')
    plt.legend()
    plt.grid(True)  # Display gridlines

    # Plot Loss with markers and grid
    plt.subplot(1, 2, 2)
    plt.plot(epochs_range, history.history['loss'][:min_val_loss_epoch], 'o-', labe
    plt.plot(epochs_range, history.history['val_loss'][:min_val_loss_epoch], marker
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.title(f'Loss up to Best Epoch ({min_val_loss_epoch})')
    plt.legend()
    plt.grid(True)  # Display gridlines

    plt.tight_layout()
    plt.show()

# Call the function with the history variable
plot_history_until_best_epoch_modified(history)
```



In [ ]:
```
# PLOT THE TRAINING AND VALIDATION CURVES

# Prepare the figure
plt.figure(figsize=(12, 4))

# Plot Training and Validation Accuracy
plt.subplot(1, 2, 1)  # 1 row, 2 columns, 1st subplot
plt.plot(history.history['accuracy'], 'o-', label='Training Accuracy')  # Circle ma
plt.plot(history.history['val_accuracy'], '^', linestyle='--', fillstyle='none', la
plt.title('Model Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend(loc='lower right')
plt.grid(True)  # Display gridlines

# Plot Training and Validation Loss
plt.subplot(1, 2, 2)  # 1 row, 2 columns, 2nd subplot
plt.plot(history.history['loss'], 'o-', label='Training Loss')  # Circle markers, s
plt.plot(history.history['val_loss'], marker='^', linestyle='--', fillstyle='none',
plt.title('Model Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend(loc='upper right')
plt.grid(True)  # Display gridlines

# Display the plots
plt.tight_layout()
plt.show()
```



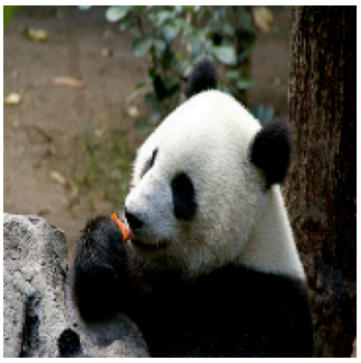
In [ ]:
```
# Assuming test_dataset is batched: (image, label)
predictions = []
labels = []
images = []
for img, label in test_dataset.take(10):  # Adjust the number of batches to suit yo
    pred = pvcm2.predict(img)
    pred = np.round(pred).astype(int).flatten()  # Round predictions to 0 or 1 for
    predictions.extend(pred)
    labels.extend(label.numpy())
    images.extend(img.numpy())

# Convert lists to arrays for easier manipulation
predictions = np.array(predictions)
labels = np.array(labels)
```

```python
images = np.array(images)

# Find indices of correct and incorrect predictions
correct_indices = np.where(predictions == labels)[0]
incorrect_indices = np.where(predictions != labels)[0]

# Function to plot images
def plot_images(indices, title):
    plt.figure(figsize=(15, 5))
    for i, idx in enumerate(indices[:3], start=1):  # Plot up to 3 images
        plt.subplot(1, 3, i)
        # Rescale the images back to 0-255 and convert to integers for display
        image_to_display = (images[idx] * 255).astype("uint8")
        plt.imshow(image_to_display)
        plt.title(f"Predicted: {predictions[idx]}, Actual: {labels[idx]}")
        plt.axis("off")
    plt.suptitle(title)
    plt.show()


# Plot correct classifications
plot_images(correct_indices, "Correct Classifications")

# Plot incorrect classifications
plot_images(incorrect_indices, "Incorrect Classifications")
```

```
1/1 [==============================] - 0s 81ms/step
1/1 [==============================] - 0s 23ms/step
1/1 [==============================] - 0s 23ms/step
1/1 [==============================] - 0s 23ms/step
1/1 [==============================] - 0s 24ms/step
1/1 [==============================] - 0s 23ms/step
1/1 [==============================] - 0s 79ms/step
```

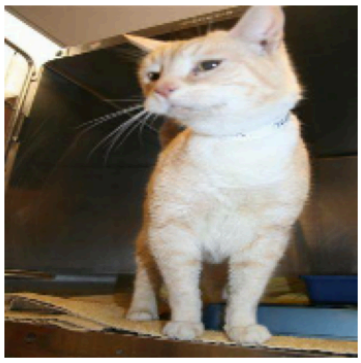
Correct Classifications

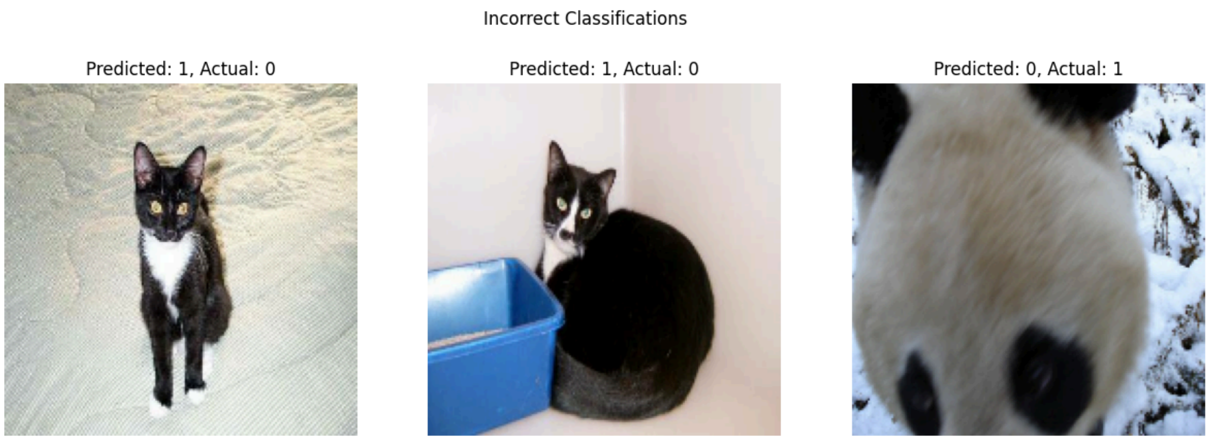
Predicted: 1, Actual: 1



Predicted: 0, Actual: 0

Predicted: 0, Actual: 0





PART II.3 DOGS VERSUS PANDAS CLASSIFIER (pvcm3)

Develop a third, best CNN

RESTRICTIONS:

NONE

pvcm3 Architecture:

- 2D Convolutional Neural Network (CNN)

** L2 (Ridge) Regularizer of 1×10^-4 ** 3x3 Kernels/Filters (32 of them) ** MaxPool 2D Layer (size 2) ** Dropout Layer of 0.25 (25%)

- 2D Convolutional Neural Network (CNN)

** L2 (Ridge) Regularizer of 1×10^-4 ** 3x3 Kernels/Filters (32 of them) ** MaxPool 2D Layer (size 2) ** Dropout Layer of 0.25 (25%)

- 2D Convolutional Neural Network (CNN)

** L2 (Ridge) Regularizer of 1×10^-4 ** 3x3 Kernels/Filters (32 of them) ** MaxPool 2D Layer (size 2) ** Dropout Layer of 0.25 (25%)

- Flattening Layer (Rank-1 Tensor)
- Dropout Layer of 0.50 (50%)
- Fully-Connected/Dense Network (DNN)

** HL01: 128 PE with ReLU activation ** OL: 1 PE with Sigmoid activation

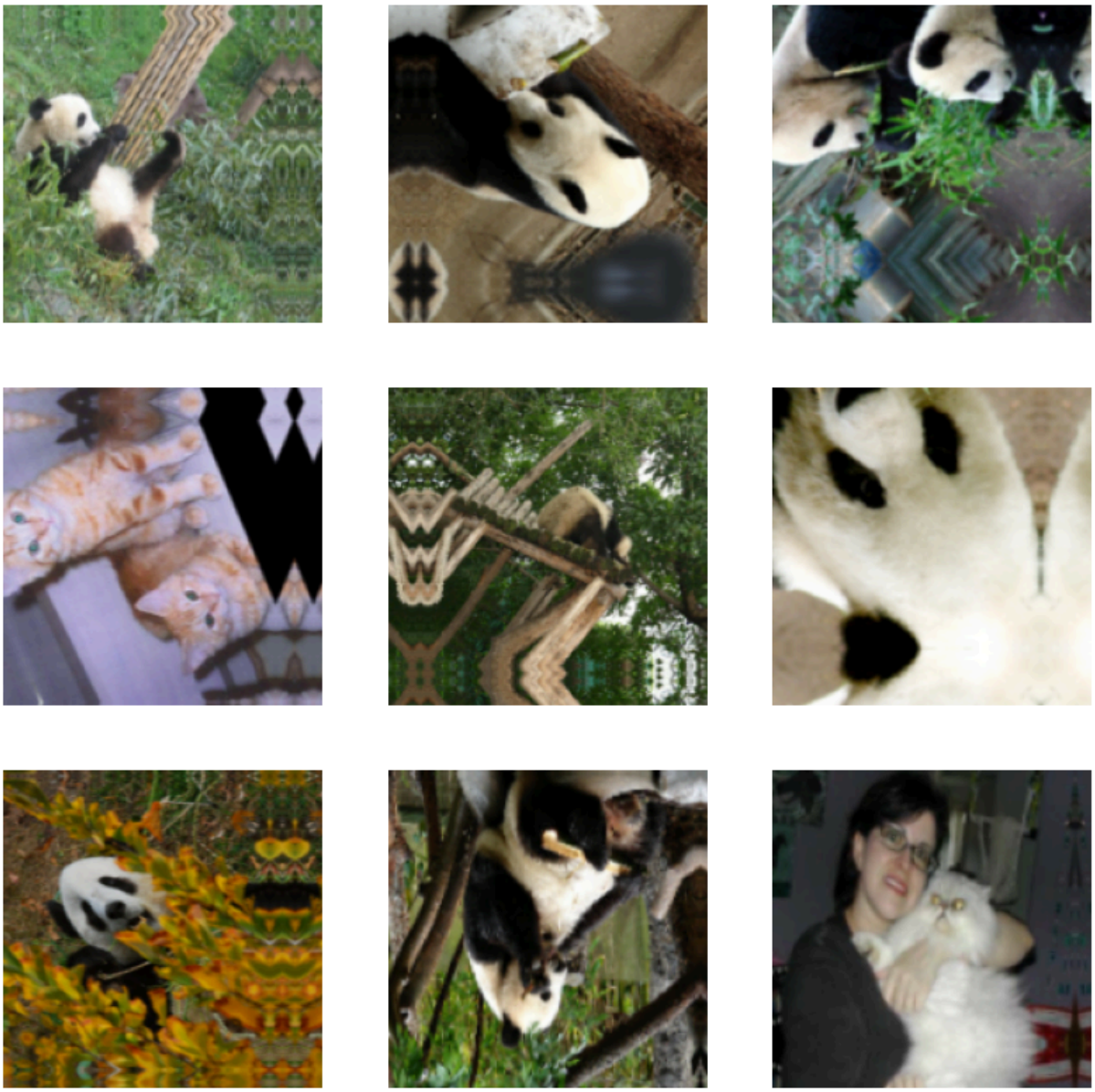
Additionally, input data was artificially augmented

In [ ]:
```
data_augmentation = tf.keras.Sequential([
  layers.experimental.preprocessing.RandomFlip("horizontal_and_vertical"),
  layers.experimental.preprocessing.RandomRotation(0.2),
  layers.experimental.preprocessing.RandomZoom(0.2),
```

```
  layers.experimental.preprocessing.RandomTranslation(height_factor=0.2, width_fact
])
```

In [ ]:
```
# Assuming train_dataset is your TensorFlow dataset for training
def augment(image, label):
    # Apply the data augmentation to the images
    image = data_augmentation(image)
    return image, label

train_dataset_augmented = train_dataset.map(augment)
```

In [ ]:
```
import matplotlib.pyplot as plt

for images, _ in train_dataset_augmented.take(1):
    plt.figure(figsize=(10, 10))
    for i in range(9):  # Display 9 images from the batch
        ax = plt.subplot(3, 3, i + 1)
        # Scale the images back to [0, 255] for correct visualization
        plt.imshow((images[i].numpy() * 255).astype("uint8"))
        plt.axis("off")
    plt.show()
```



In [ ]:
```
# DEFINE MODEL ARCHITECTURE FOR pvcm02 USING KERAS SEQUENTIAL API
pvcm3 = Sequential([
    Conv2D(32, (3, 3), activation='relu', kernel_regularizer=l2(1E-4), input_shape=
    MaxPooling2D((2, 2)),
    Dropout(0.25), # dropout of 25% after first pooling
    Conv2D(64, (3, 3), activation='relu', kernel_regularizer=l2(1E-4)),
    MaxPooling2D((2, 2)),
    Dropout(0.25), # dropout of 25% after second pooling
    Conv2D(128, (3, 3), activation='relu', kernel_regularizer=l2(1E-4)),
    MaxPooling2D((2, 2)),
    Dropout(0.25), # dropout of 25% after third pooling
    Flatten(),
    Dense(128, activation='relu', kernel_regularizer=l2(1E-4)),
    Dropout(0.5), # dropout of 50% before output
    Dense(1, activation='sigmoid')
])
```

In [ ]:
```
# COMPILE THE MODEL
pvcm3.compile(optimizer='adam',
```

```
              loss='binary_crossentropy',
              metrics=['accuracy'])
```

In [ ]:
```
# SET UP CALLBACK SO THAT WE CAN RETURN THE MODEL (.KERAS) FILE WHOSE WEIGHTS ACHIE

# SPECIFY THE PATH TO SAVE THE BEST MODEL
model_save_path = "best_model.keras"

# SET UP THE MODEL_CHECKPOINT_CALLBACK MONITORING THE VAL_LOSS
model_checkpoint_callback = ModelCheckpoint(
    filepath=model_save_path,
    save_best_only=True,
    monitor='val_loss',
    mode='min',
    verbose=1
)
```

In [ ]:
```
# FIT THE MODEL
history = pvcm3.fit(train_dataset,
                    epochs=50,
                    validation_data=validation_dataset,
                    callbacks=[model_checkpoint_callback])
```

In [ ]:
```
# PRINT THE MODEL SUMMARY
pvcm3.summary()
```

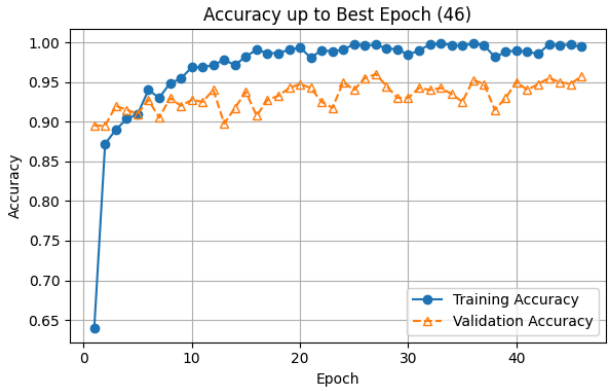
```
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_6 (Conv2D)           (None, 178, 178, 32)      896

 max_pooling2d_6 (MaxPoolin  (None, 89, 89, 32)        0
 g2D)

 dropout_4 (Dropout)         (None, 89, 89, 32)        0

 conv2d_7 (Conv2D)           (None, 87, 87, 64)        18496

 max_pooling2d_7 (MaxPoolin  (None, 43, 43, 64)        0
 g2D)

 dropout_5 (Dropout)         (None, 43, 43, 64)        0

 conv2d_8 (Conv2D)           (None, 41, 41, 128)       73856

 max_pooling2d_8 (MaxPoolin  (None, 20, 20, 128)       0
 g2D)

 dropout_6 (Dropout)         (None, 20, 20, 128)       0

 flatten_2 (Flatten)         (None, 51200)             0

 dense_4 (Dense)             (None, 128)               6553728

 dropout_7 (Dropout)         (None, 128)               0

 dense_5 (Dense)             (None, 1)                 129

=================================================================
Total params: 6647105 (25.36 MB)
Trainable params: 6647105 (25.36 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

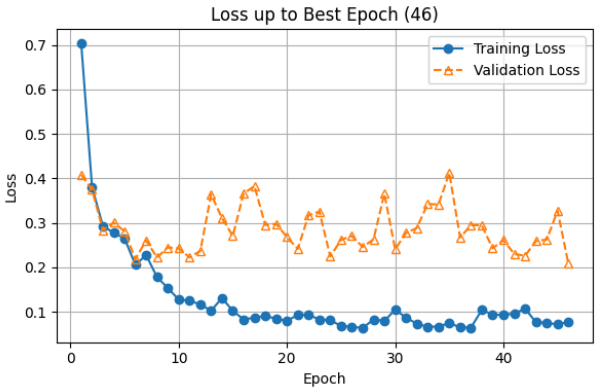
In [ ]:
```python
# EVALUATE THE MODEL
test_loss, test_accuracy = pvcm3.evaluate(test_dataset)
print(f'Test Loss: {test_loss}')
print(f'Test Accuracy: {test_accuracy}')
```

```
7/7 [==============================] - 0s 6ms/step - loss: 0.3316 - accuracy: 0.9450
Test Loss: 0.33160948753356934
Test Accuracy: 0.9449999928474426
```

In [ ]:
```python
def plot_history_until_best_epoch_modified(history):
    # Find the epoch number where the validation loss was minimum; epochs are 1-ind
    min_val_loss_epoch = history.history['val_loss'].index(min(history.history['val

    # Prepare the range for plotting
    epochs_range = range(1, min_val_loss_epoch + 1)

    plt.figure(figsize=(12, 4))
```

```
    # Plot Accuracy with markers and grid
    plt.subplot(1, 2, 1)
    plt.plot(epochs_range, history.history['accuracy'][:min_val_loss_epoch], 'o-',
    plt.plot(epochs_range, history.history['val_accuracy'][:min_val_loss_epoch], ma
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.title(f'Accuracy up to Best Epoch ({min_val_loss_epoch})')
    plt.legend()
    plt.grid(True)  # Display gridlines

    # Plot Loss with markers and grid
    plt.subplot(1, 2, 2)
    plt.plot(epochs_range, history.history['loss'][:min_val_loss_epoch], 'o-', labe
    plt.plot(epochs_range, history.history['val_loss'][:min_val_loss_epoch], marker
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.title(f'Loss up to Best Epoch ({min_val_loss_epoch})')
    plt.legend()
    plt.grid(True)  # Display gridlines

    plt.tight_layout()
    plt.show()

# Call the function with the history variable
plot_history_until_best_epoch_modified(history)
```

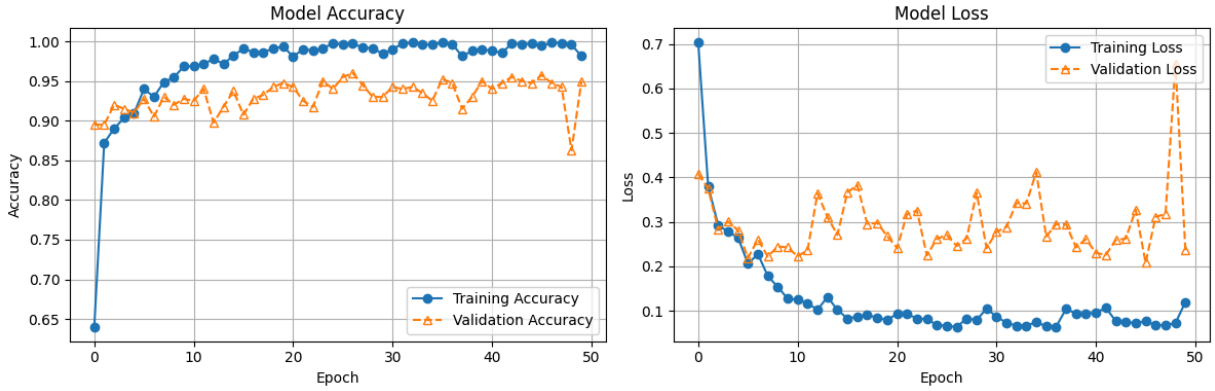




In [ ]:

```
# PLOT THE TRAINING AND VALIDATION CURVES

# Prepare the figure
plt.figure(figsize=(12, 4))

# Plot Training and Validation Accuracy
plt.subplot(1, 2, 1)  # 1 row, 2 columns, 1st subplot
plt.plot(history.history['accuracy'], 'o-', label='Training Accuracy')  # Circle ma
plt.plot(history.history['val_accuracy'], '^', linestyle='--', fillstyle='none', la
plt.title('Model Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend(loc='lower right')
plt.grid(True)  # Display gridlines

# Plot Training and Validation Loss
```

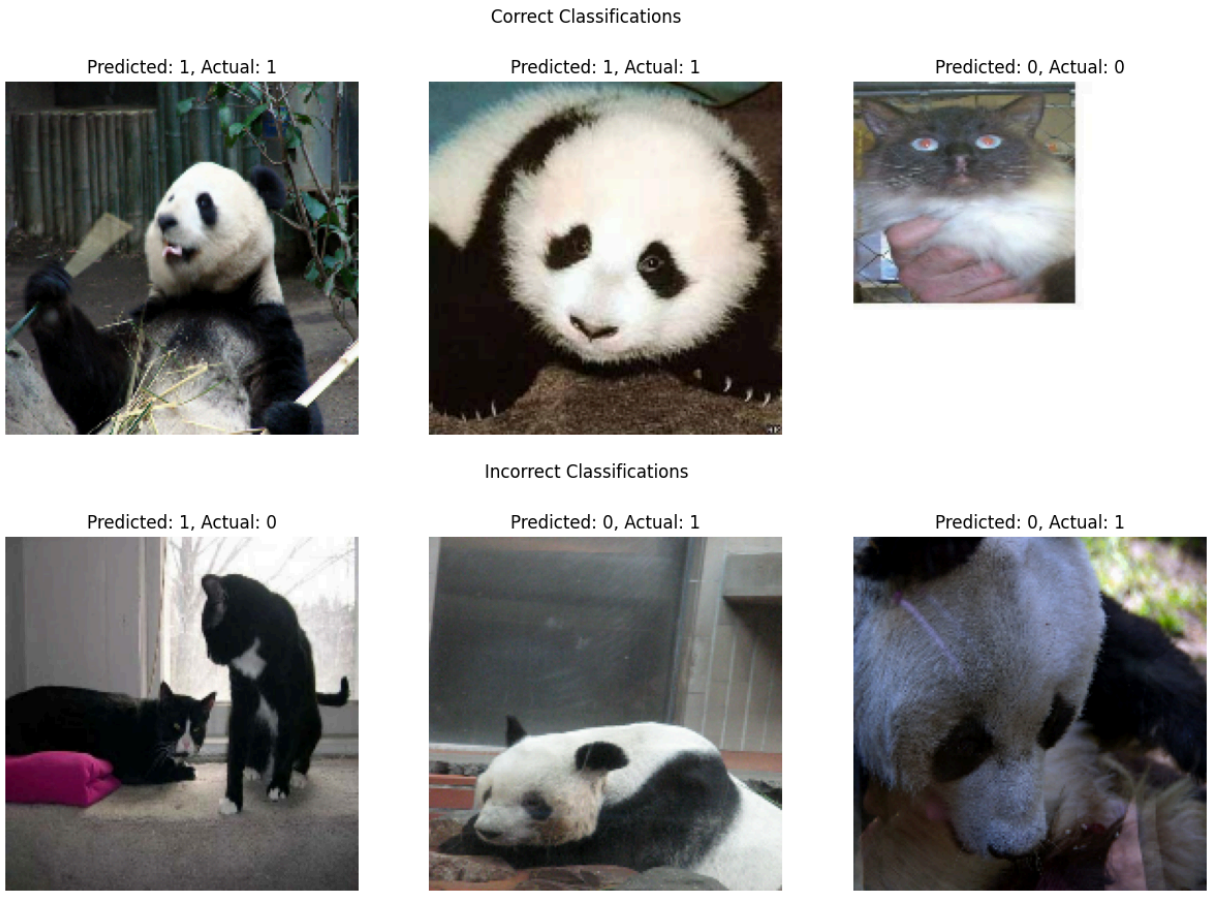
```
plt.subplot(1, 2, 2)  # 1 row, 2 columns, 2nd subplot
plt.plot(history.history['loss'], 'o-', label='Training Loss')  # Circle markers, s
plt.plot(history.history['val_loss'], marker='^', linestyle='--', fillstyle='none',
plt.title('Model Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend(loc='upper right')
plt.grid(True)  # Display gridlines

# Display the plots
plt.tight_layout()
plt.show()
```



In [ ]:
```
# Assuming test_dataset is batched: (image, label)
predictions = []
labels = []
images = []
for img, label in test_dataset.take(10):  # Adjust the number of batches to suit yo
    pred = pvcm3.predict(img)
    pred = np.round(pred).astype(int).flatten()  # Round predictions to 0 or 1 for
    predictions.extend(pred)
    labels.extend(label.numpy())
    images.extend(img.numpy())

# Convert lists to arrays for easier manipulation
predictions = np.array(predictions)
labels = np.array(labels)
images = np.array(images)

# Find indices of correct and incorrect predictions
correct_indices = np.where(predictions == labels)[0]
incorrect_indices = np.where(predictions != labels)[0]

# Function to plot images
def plot_images(indices, title):
    plt.figure(figsize=(15, 5))
    for i, idx in enumerate(indices[:3], start=1):  # Plot up to 3 images
        plt.subplot(1, 3, i)
        # Rescale the images back to 0-255 and convert to integers for display
        image_to_display = (images[idx] * 255).astype("uint8")
        plt.imshow(image_to_display)
        plt.title(f"Predicted: {predictions[idx]}, Actual: {labels[idx]}")
        plt.axis("off")
```

```
    plt.suptitle(title)
    plt.show()


# Plot correct classifications
plot_images(correct_indices, "Correct Classifications")

# Plot incorrect classifications
plot_images(incorrect_indices, "Incorrect Classifications")
```

```
WARNING:tensorflow:5 out of the last 15 calls to <function Model.make_predict_functi
on.<locals>.predict_function at 0x7cd3e3f3da20> triggered tf.function retracing. Tra
cing is expensive and the excessive number of tracings could be due to (1) creating
@tf.function repeatedly in a loop, (2) passing tensors with different shapes, (3) pa
ssing Python objects instead of tensors. For (1), please define your @tf.function ou
tside of the loop. For (2), @tf.function has reduce_retracing=True option that can a
void unnecessary retracing. For (3), please refer to https://www.tensorflow.org/guid
e/function#controlling_retracing and https://www.tensorflow.org/api_docs/python/tf/f
unction for  more details.
1/1 [==============================] - 0s 82ms/step
1/1 [==============================] - 0s 24ms/step
1/1 [==============================] - 0s 23ms/step
1/1 [==============================] - 0s 24ms/step
1/1 [==============================] - 0s 24ms/step
1/1 [==============================] - 0s 23ms/step
1/1 [==============================] - 0s 78ms/step
```



In [ ]:
```
# RANDOM CLASSIFIER
# Assuming test_dataset is batched
```

```python
num_samples = sum([batch[0].shape[0] for batch in test_dataset])

# Generate random predictions for binary classification
random_predictions_binary = tf.random.uniform(shape=[num_samples], minval=0, maxval

# Collect actual labels from the dataset
actual_labels = []
for _, label in test_dataset:
    # Flatten the batch of labels into a list
    actual_labels.extend(label.numpy().flatten())  # Use .flatten() to ensure it's

# Ensure actual_labels is a TensorFlow tensor to match random_predictions_binary
actual_labels = tf.convert_to_tensor(actual_labels, dtype=tf.int32)

# Calculate accuracy
accuracy = tf.reduce_mean(tf.cast(tf.equal(random_predictions_binary, actual_labels
print(f"Random Classifier Accuracy: {accuracy.numpy()}")
```

```
Random Classifier Accuracy: 0.4749999940395355
```