Convolutional Neural Network

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

A Dataset of Sea creatures with 4 classes and a minimum of 400 images for each class

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense,Dropout,Convolution2D,MaxPooling2D,Flatten
import tensorflow as tf
```

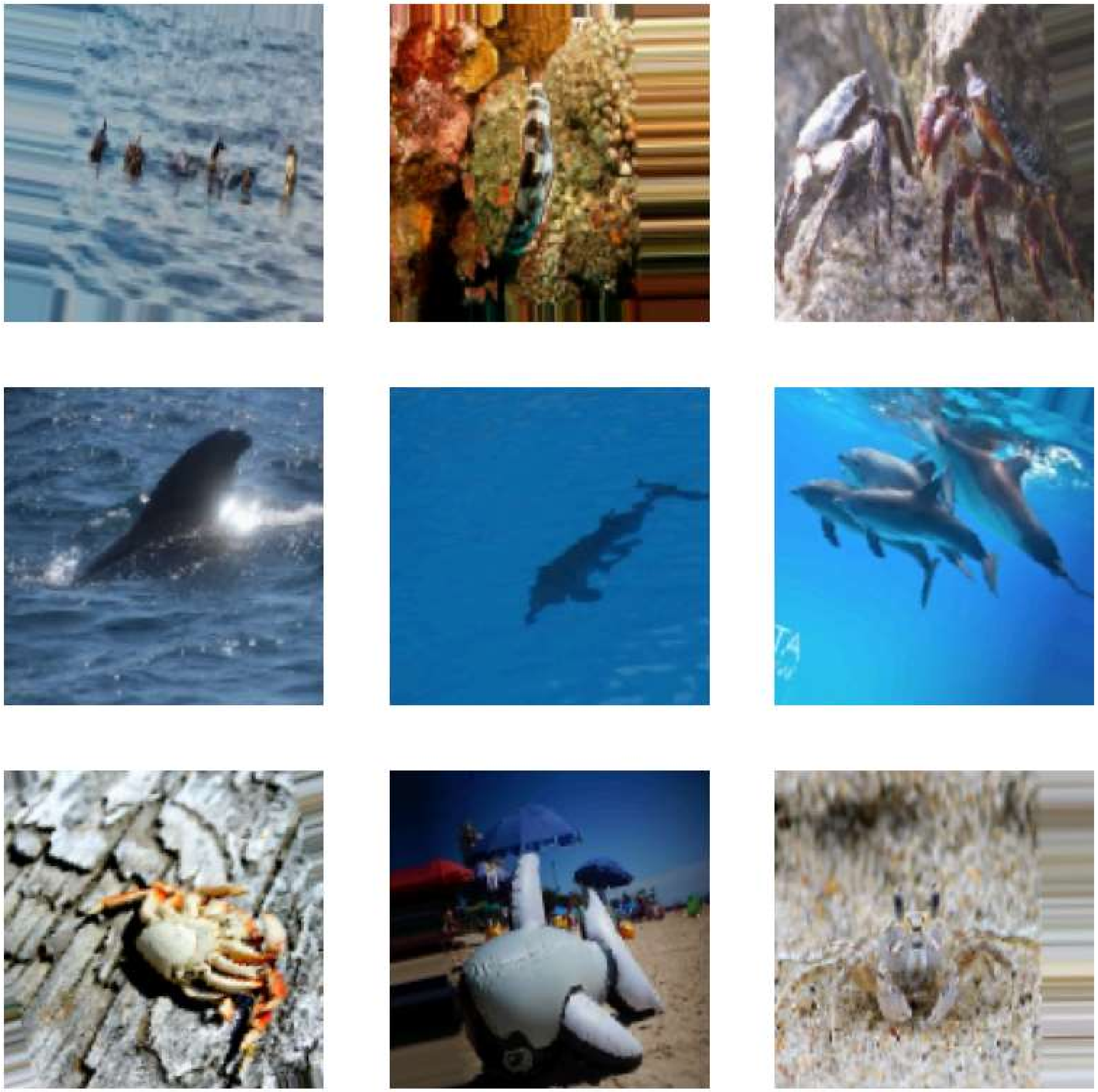
DATA PREPROCESSING

```
from tensorflow.keras.preprocessing.image import ImageDataGenerator

# Define the image size
IMAGE_SIZE = 128
augmenter = ImageDataGenerator(
        rescale=1./255,
    rotation_range=20,
    height_shift_range=0.2,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True,

)


# augmenting data
augmentedTrainSet = augmenter.flow_from_directory(
        '/content/drive/MyDrive/Dataset/Train',
        target_size=(IMAGE_SIZE,IMAGE_SIZE),
        class_mode="sparse",
        shuffle=True,
        batch_size=9
)

print(len(augmentedTrainSet))
```

```
Found 1878 images belonging to 4 classes.
209
```

Train set have 1878 images and it belongs to 4 classes

```python
# Plottting the some of the augmented dataset
import matplotlib.pyplot as plt
plt.figure(figsize=(10, 10))
for i in range(9):
    images, _ = next(augmentedTrainSet)
    plt.subplot(3, 3, i + 1)
    plt.imshow(images[0])
    plt.axis('off')
plt.show()
```



```
#Print the class names
classes = list(augmentedTrainSet.class_indices.keys())
classes
```

```
['Clams', 'Corals', 'Crabs', 'Dolphin']
```

```
testAugmenter = ImageDataGenerator(
        rescale=1./255,
        rotation_range=10,
        horizontal_flip=True)

#augmented data
augmentedTestSet = testAugmenter.flow_from_directory(
        '/content/drive/MyDrive/Dataset/Test',
        target_size=(IMAGE_SIZE,IMAGE_SIZE),
        class_mode="sparse"
)
```

```
Found 400 images belonging to 4 classes.
```

CNN MODEL

```
cnn = tf.keras.models.Sequential()
```

Convolution

```
cnn.add(tf.keras.layers.Conv2D(filters=64, kernel_size=3, activation='relu', input_shape=[128, 128, 3]))
```

Pooling

```
cnn.add(tf.keras.layers.MaxPool2D(pool_size=2, strides=2))
```

Adding a second convolutional layer

```
cnn.add(tf.keras.layers.Conv2D(filters=32, kernel_size=3, activation='relu'))
cnn.add(tf.keras.layers.MaxPool2D(pool_size=2, strides=2))
```

Adding a third convolutional layer

```
cnn.add(tf.keras.layers.Conv2D(filters=16, kernel_size=3, activation='relu'))
cnn.add(tf.keras.layers.MaxPool2D(pool_size=2, strides=1))
```

Flattening

```
cnn.add(tf.keras.layers.Flatten())
```

Full Connection

```
cnn.add(Dense(units=96, activation='relu'))
cnn.add(Dropout(0.40))
cnn.add(Dense(units=32, activation='relu'))
```

Output Layer

```
cnn.add(tf.keras.layers.Dense(units=4, activation='softmax'))
```

Compiling the CNN

```
cnn.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])
```

```
#Training the CNN
history = cnn.fit(augmentedTrainSet, validation_data=augmentedTestSet, epochs=20)
```

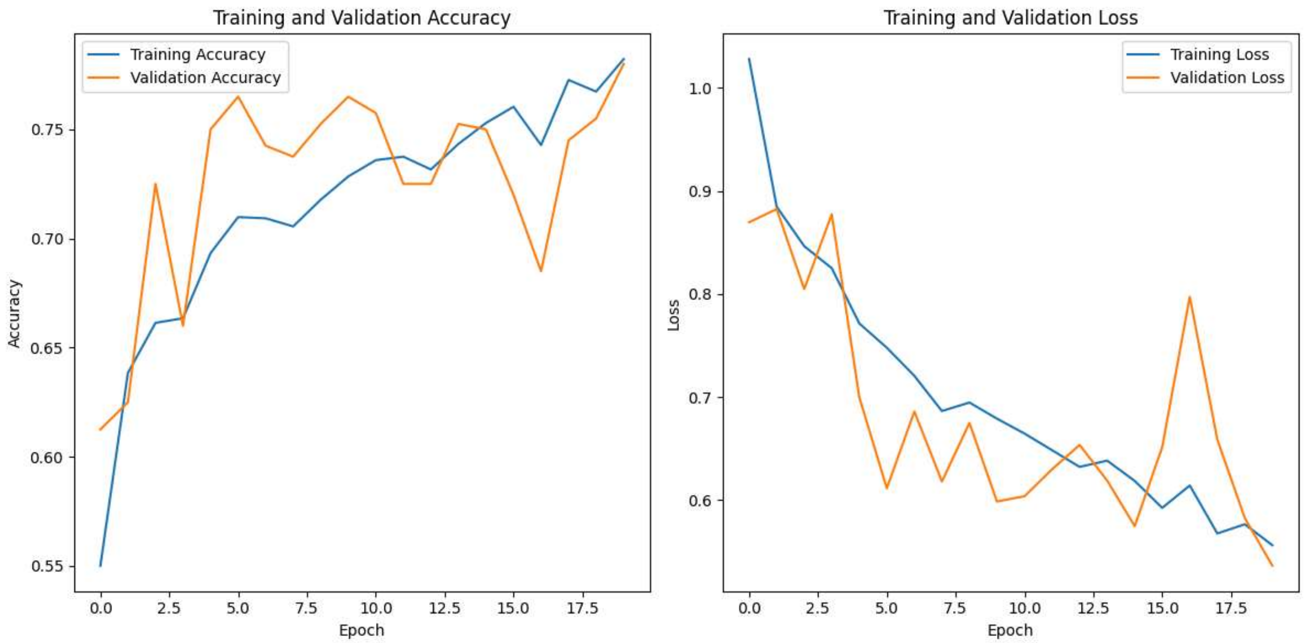
```
Epoch 1/20
209/209 [==============================] - 94s 440ms/step - loss: 1.0280 - accuracy: 0.5501 - val_loss: 0.8696 - val_accuracy: 0.6125
Epoch 2/20
209/209 [==============================] - 85s 408ms/step - loss: 0.8847 - accuracy: 0.6384 - val_loss: 0.8825 - val_accuracy: 0.6250
Epoch 3/20
209/209 [==============================] - 88s 422ms/step - loss: 0.8465 - accuracy: 0.6613 - val_loss: 0.8048 - val_accuracy: 0.7250
Epoch 4/20
209/209 [==============================] - 94s 447ms/step - loss: 0.8251 - accuracy: 0.6635 - val_loss: 0.8775 - val_accuracy: 0.6600
Epoch 5/20
209/209 [==============================] - 78s 375ms/step - loss: 0.7715 - accuracy: 0.6933 - val_loss: 0.6999 - val_accuracy: 0.7500
Epoch 6/20
209/209 [==============================] - 84s 402ms/step - loss: 0.7479 - accuracy: 0.7098 - val_loss: 0.6115 - val_accuracy: 0.7650
Epoch 7/20
209/209 [==============================] - 83s 395ms/step - loss: 0.7206 - accuracy: 0.7093 - val_loss: 0.6860 - val_accuracy: 0.7425
Epoch 8/20
209/209 [==============================] - 83s 397ms/step - loss: 0.6865 - accuracy: 0.7055 - val_loss: 0.6181 - val_accuracy: 0.7375
Epoch 9/20
209/209 [==============================] - 78s 373ms/step - loss: 0.6947 - accuracy: 0.7178 - val_loss: 0.6749 - val_accuracy: 0.7525
Epoch 10/20
209/209 [==============================] - 88s 420ms/step - loss: 0.6790 - accuracy: 0.7284 - val_loss: 0.5986 - val_accuracy: 0.7650
Epoch 11/20
209/209 [==============================] - 76s 362ms/step - loss: 0.6646 - accuracy: 0.7359 - val_loss: 0.6038 - val_accuracy: 0.7575
Epoch 12/20
209/209 [==============================] - 81s 385ms/step - loss: 0.6484 - accuracy: 0.7375 - val_loss: 0.6299 - val_accuracy: 0.7250
Epoch 13/20
```

```
209/209 [==============================] - 83s 397ms/step - loss: 0.6323 - accuracy: 0.7316 - val_loss: 0.6536 - val_accuracy: 0.7250
Epoch 14/20
209/209 [==============================] - 81s 386ms/step - loss: 0.6383 - accuracy: 0.7433 - val_loss: 0.6190 - val_accuracy: 0.7525
Epoch 15/20
209/209 [==============================] - 81s 387ms/step - loss: 0.6187 - accuracy: 0.7529 - val_loss: 0.5747 - val_accuracy: 0.7500
Epoch 16/20
209/209 [==============================] - 87s 418ms/step - loss: 0.5925 - accuracy: 0.7604 - val_loss: 0.6515 - val_accuracy: 0.7200
Epoch 17/20
209/209 [==============================] - 81s 385ms/step - loss: 0.6142 - accuracy: 0.7428 - val_loss: 0.7973 - val_accuracy: 0.6850
Epoch 18/20
209/209 [==============================] - 79s 375ms/step - loss: 0.5676 - accuracy: 0.7726 - val_loss: 0.6587 - val_accuracy: 0.7450
Epoch 19/20
209/209 [==============================] - 80s 383ms/step - loss: 0.5766 - accuracy: 0.7673 - val_loss: 0.5825 - val_accuracy: 0.7550
Epoch 20/20
209/209 [==============================] - 79s 379ms/step - loss: 0.5562 - accuracy: 0.7822 - val_loss: 0.5363 - val_accuracy: 0.7800
```

Visualizing training/validation loss and accuracy.

```python
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, confusion_matrix
```

```python
plt.figure(figsize=(12, 6))

# training and validation accuracy
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

# training and validation loss
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

plt.tight_layout()
plt.show()
```



EVALUATION

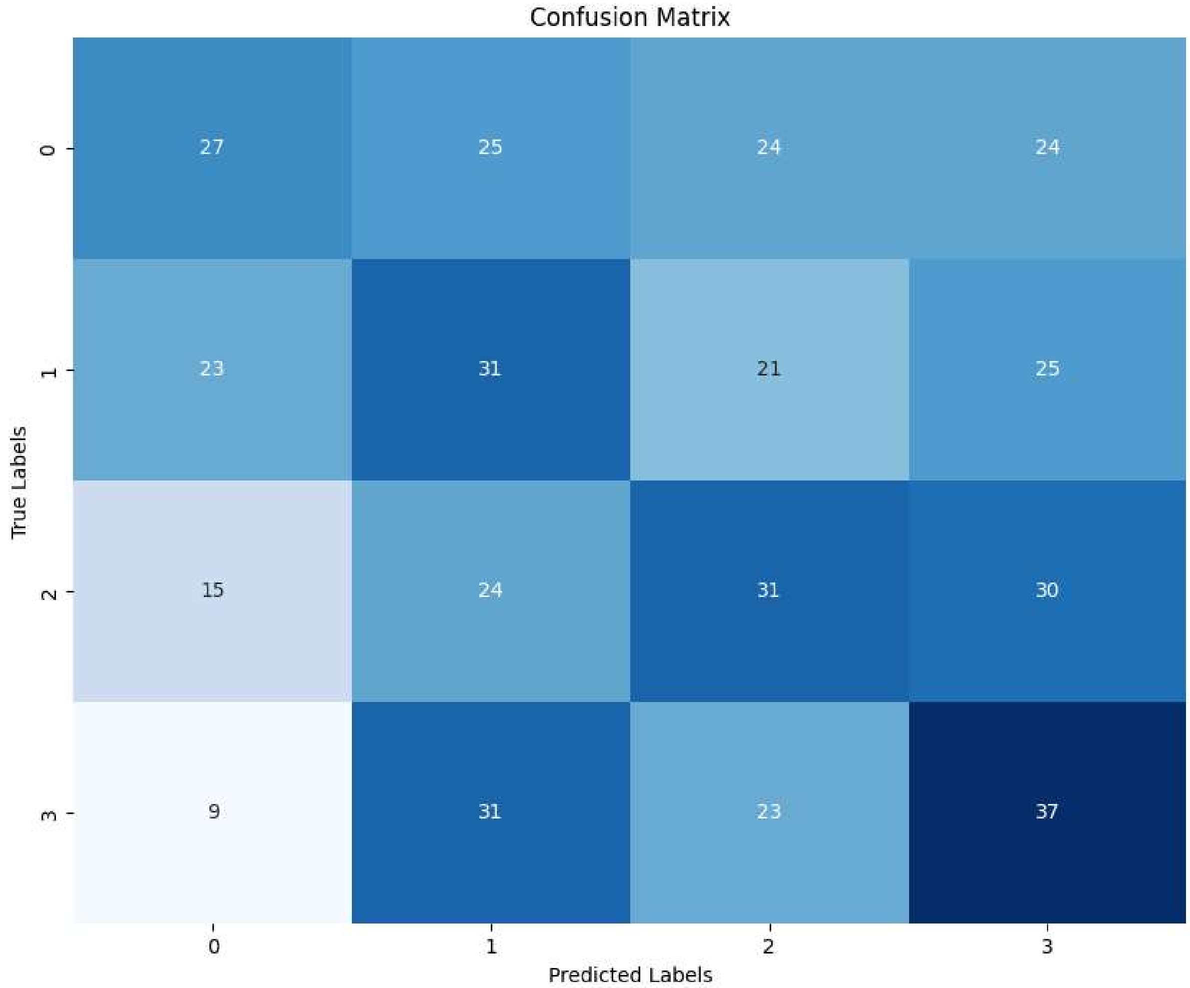
Evaluate the performance of your trained model on the test dataset

```
# Evaluate the model on the test dataset
evaluation = cnn.evaluate(augmentedTestSet)

# Print the evaluation results
print("Test Loss:", evaluation[0])
print("Test Accuracy:", evaluation[1])
```

```
13/13 [==============================] - 6s 441ms/step - loss: 0.5274 - accuracy: 0.7825
Test Loss: 0.5273718237876892
Test Accuracy: 0.7825000286102295
```

```python
# Calculate additional evaluation metrics

# Predict classes for test data
test_predictions = np.argmax(cnn.predict(augmentedTestSet), axis=-1)
true_classes = augmentedTestSet.classes

# Evaluation metrics
precision = precision_score(true_classes, test_predictions, average='weighted')
recall = recall_score(true_classes, test_predictions, average='weighted')
f1 = f1_score(true_classes, test_predictions, average='weighted')

print("Precision:", precision)
print("Recall:", recall)
print("F1 Score:", f1)

# Confusion matrix
plt.figure(figsize=(10, 8))
sns.heatmap(confusion_matrix(true_classes, test_predictions), annot=True, fmt='d', cmap='Blues', cbar=False)
plt.title('Confusion Matrix')
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.show()
```

```
13/13 [==============================] - 9s 662ms/step
Precision: 0.31906024362920915
Recall: 0.315
F1 Score: 0.31458351792069117
```



PREDICTING THE SEA CREATURES

```
def predict(model, img):
    img_array = tf.keras.preprocessing.image.img_to_array(images[i])
    img_array = tf.expand_dims(img_array, 0)

    predictions = model.predict(img_array)

    predicted_class = classes[np.argmax(predictions[0])]
    confidence = round(100 * (np.max(predictions[0])), 2)
```

```
    return predicted_class, confidence


# Visualizing predictions

plt.figure(figsize=(15, 15))
for images, labels in augmentedTestSet:
    for i in range(6):
        ax = plt.subplot(3, 3, i + 1)
        plt.imshow(images[i])

        predicted_class, confidence = predict(cnn, images[i])
        actual_class = classes[int(labels[i])]

        plt.title(f"Actual: {actual_class},\n Predicted: {predicted_class}.\n Confidence: {confidence}%")

        plt.axis("off")
    break
```

```
1/1 [==============================] - 0s 131ms/step
1/1 [==============================] - 0s 26ms/step
1/1 [==============================] - 0s 29ms/step
1/1 [==============================] - 0s 26ms/step
1/1 [==============================] - 0s 29ms/step
1/1 [==============================] - 0s 28ms/step
```

Actual: Clams,
Predicted: Corals.
Confidence: 60.02%

Actual: Dolphin,
Predicted: Dolphin.
Confidence: 96.78%

Actual: Crabs,
Predicted: Crabs.
Confidence: 85.89%

Results Interpretation

Interpretation of Performance Metrics:

The accuracy of the model is 78% but while predicting classes other than dolphins such as clams, corals, crabs the model tends to have less confidence and tend to predict wrong class this might be due to imbalanced dataset.

Challenges Encountered: