CNN Classification Project

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Problem Statement

- Develop a machine learning model that accurately classifies 525 different types of birds We will employ cross-validation as the benchmark for evaluating model performance. The model is trained on the training data, validated on the validation set to fine-tune hyperparameters, and finally evaluated on the unseen testing set to assess its generalizability.The data source is the 525-bird-species dataset from Kaggle. It consists of labeled images categorized into 525 bird species. We anticipate encountering common image classification challenges like variations in lighting, pose, and background clutter.The project's goal is to build a robust CNN model that can achieve high accuracy in classifying bird species from images. This model could potentially be used for various applications, such as automated bird identification in ecological surveys or educational tools for bird enthusiasts.

Dataset

Overview

The dataset used for this project is the "525-bird-species" dataset from Kaggle, ideal for image recognition and classification projects.

- 525 bird species total
- 84635 training images
- 2625 test images (5 per species)
- 2625 validation images (5 per species)

Columns

- class id: class index value
- filepaths: file path for each image (eg. 'train/ABBOTTS BABBLER/001.jpg')
- label: bird species label
- data set: which data set the image belongs to (train/test/other)
- scientific name: scientific name of bird species

Benchmarks and Evaluation

The dataset is split into training, testing, and validation sets which will allow us to effectively train our model and evaluate our test set. Our main benchmark will be how accurately we can classify the images into the correct bird species. As mentioned above, we will be cross validating to make sure our model's performance is consistent.

```
from google.colab import files
files.upload()
```

Choose Files no files selected Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
! mkdir ~/.kaggle
! cp kaggle.json ~/.kaggle/
! chmod 600 ~/.kaggle/kaggle.json
```

```
!kaggle datasets download -d gpiosenka/100-bird-species
```

```
Downloading 100-bird-species.zip to /content
100% 1.95G/1.96G [01:05<00:00, 31.2MB/s]
100% 1.96G/1.96G [01:05<00:00, 31.8MB/s]
```

```
!unzip 100-bird-species.zip
```

```
Streaming output truncated to the last 5000 lines.
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inflating: train/WHITE THROATED BEE EATER/002.jpg
inflating: train/WHITE THROATED BEE EATER/003.jpg
```

```
import tensorflow as tf
import matplotlib.pyplot as plt
import numpy as np
from tensorflow.keras.utils import image_dataset_from_directory
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
```

Loads images into dataframes

```
train_dataset = image_dataset_from_directory(
 "/content/train",
    image_size=(224, 224),
    shuffle=True,  # Shuffle for better mixing
    batch_size=32)

test_dataset = image_dataset_from_directory(
 "/content/test",
    image_size=(224, 224),
    batch_size=32)

vaild_dataset = image_dataset_from_directory(
 "/content/valid",
    image_size=(224, 224),
    batch_size=32)

print(train_dataset)
```

```
Found 84635 files belonging to 525 classes.
Found 2625 files belonging to 525 classes.
Found 2625 files belonging to 525 classes.
<_PrefetchDataset element_spec=(TensorSpec(shape=(None, 224, 224, 3), dtype=t
```

Exploratory Data Analysis

- 1. Sample Images: Graph: Grid of images showcasing examples from various bird species.

  Why: This provides a visual sense of the dataset's content, image quality, and diversity in bird poses, backgrounds, and lighting conditions.

- 2. Data Preprocessing Steps: Method: Normalizng Images and Data Augmentation

  Why: Preprocessing helps standardize the data and improve training efficiency. Normalization aids in faster convergence and data augmentation artificially increases data volume and enhances model robustness.

- 3. Number of Instances per Classes

  Why: If there is an imbalance it can lead a CNN to prioritizing the majority class during training, harming its ability to recognize the minority class accurately.

Data Preprocessing

Dimensionality Reduction

Typically, CNN projects do not use traditional dimensionality reduction techniques because convolutional neural networks perform reduction. The convolutional layers effectively reduce the dimensionality of the input images while capturing the essential feature of the image (texture, edges, shapes, etc).

Scaling

Unlike dimensionality reduction, scaling is an important and distinct step in CNN. Below we have normalized the images by scaling the pixel values to a range from 0 to 1. This helps with faster convergence during training.

Displays 12 images from training data

```
for images, labels in train_dataset.take(1):
    plt.figure(figsize=(10, 10))
    for i in range(12):
        ax = plt.subplot(3, 4, i + 1)
        plt.imshow(images[i].numpy().astype("uint8"))
        plt.title(train_dataset.class_names[labels[i]])
        plt.axis("off")
    plt.show()
```

MASKED BOOBY

WHITE BREASTED WATERHEN

BREWERS BLACKBIRD

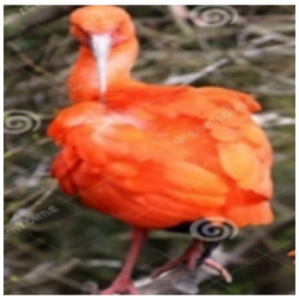
EASTERN ROSELLA

REGENT BOWERBIRD

PLUSH CRESTED JAY

MALACHITE KINGFISHER

SCARLET IBIS



AMERICAN AVOCET

BLUE GRAY GNATCATCHER

JACK SNIPE

EURASIAN BULLFINCH

Normalization

```
scaler = tf.keras.layers.Rescaling(1./255)  # Rescale to [0, 1]
normalized_ds = train_dataset.map(lambda x, y: (scaler(x), y))

image_batch, labels_batch = next(iter(normalized_ds))
first_image = image_batch[0]

# Now print the minimum and maximum values of the normalized image
print(np.min(first_image), np.max(first_image))
```

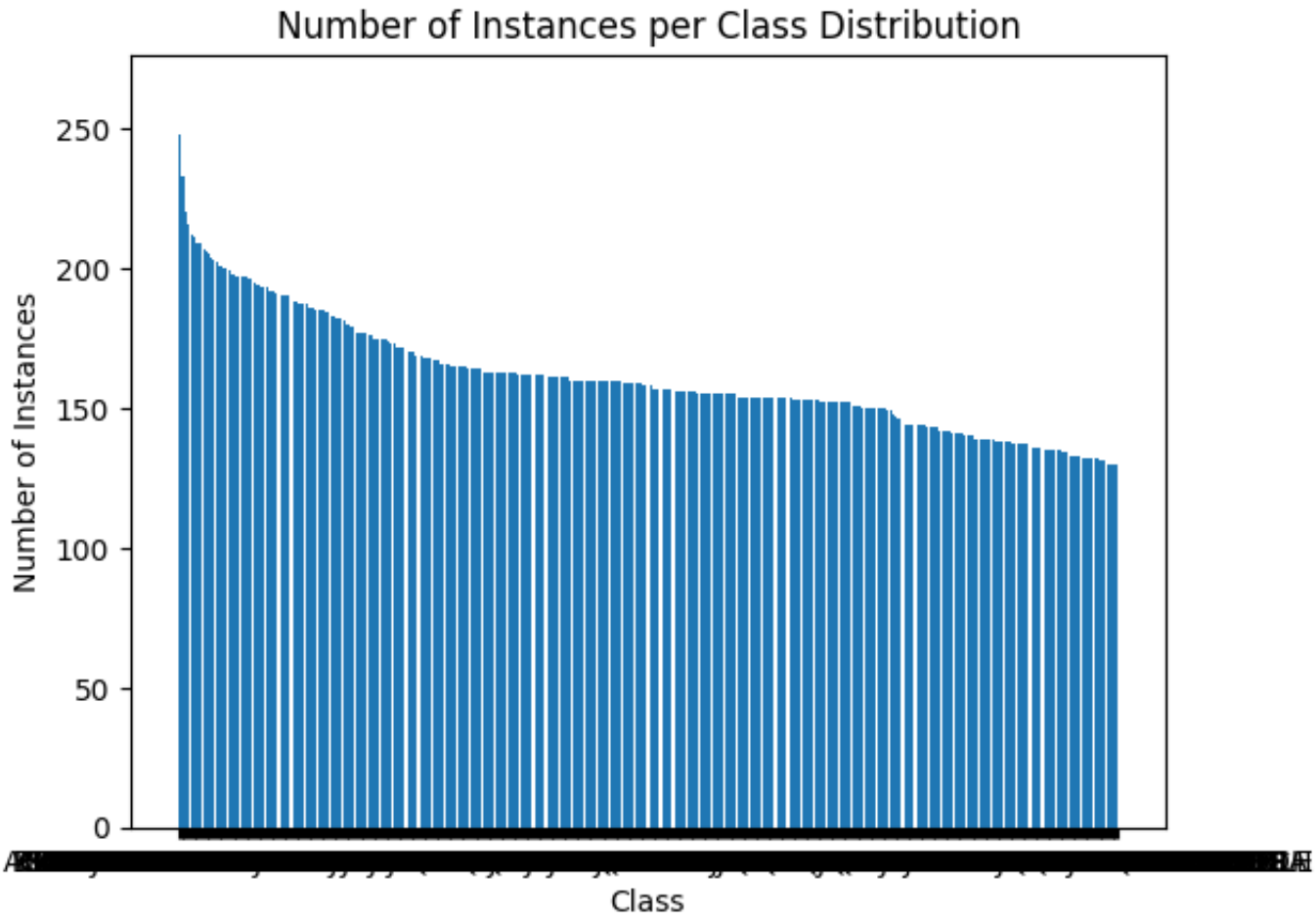
```
0.0 1.0
```

Checking Instances per class

```
import pandas as pd

df = pd.read_csv("/content/drive/MyDrive/BIRDS/100-bird-species/birds.csv")
df.head()
```

	class id	filepaths	labels	data set	scientific name
0	0.0	train/ABBOTTS BABBLER/001.jpg	ABBOTTS BABBLER	train	MALACOCINCLA ABBOTTI
1	0.0	train/ABBOTTS BABBLER/007.jpg	ABBOTTS BABBLER	train	MALACOCINCLA ABBOTTI
2	0.0	train/ABBOTTS BABBLER/008.jpg	ABBOTTS BABBLER	train	MALACOCINCLA ABBOTTI

```
df_training = df[df['data set'] == 'train']
# Get the number of instances per class
n_instance_per_class = df_training['labels'].value_counts()

# Create a bar chart
plt.bar(n_instance_per_class.index, n_instance_per_class.values)
plt.xlabel("Class")
plt.ylabel("Number of Instances")
plt.title("Number of Instances per Class Distribution")
plt.show()
```



Instances evenly distubuted dont need to augment any spefeic classes

Data Augmentation

- if sucess rate isnt good enough will implement

```
Start coding or generate with AI.
```

Base CNN Model

```
def pipeline(tf_data):
    tf_data = tf_data.shuffle(100)
    tf_data = tf_data.prefetch(tf.data.experimental.AUTOTUNE)
    return tf_data

tf_train_data = pipeline(train_dataset)
tf_val_data = pipeline(vaild_dataset)

print(tf_train_data)
print(tf_val_data)
```

```
<_PrefetchDataset element_spec=(TensorSpec(shape=(None, 224, 224, 3), dtype=t
<_PrefetchDataset element_spec=(TensorSpec(shape=(None, 224, 224, 3), dtype=t
```

```
model = tf.keras.Sequential([
    tf.keras.layers.Conv2D(6, (5, 5), activation='relu', padding='same', input_sh
    tf.keras.layers.MaxPooling2D((2, 2)),

    tf.keras.layers.Conv2D(16, (5, 5), activation='relu', padding='valid'),
    tf.keras.layers.MaxPooling2D((2, 2)),

    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(120, activation='relu'),
    tf.keras.layers.Dense(84, activation='relu'),

    tf.keras.layers.Dense(525, activation='softmax'),
])
```

```
optimiser = tf.keras.optimizers.Adam(learning_rate=0.001)

model.compile(loss="sparse_categorical_crossentropy",
              optimizer="adam",
              metrics=["accuracy"])

model.summary()
```

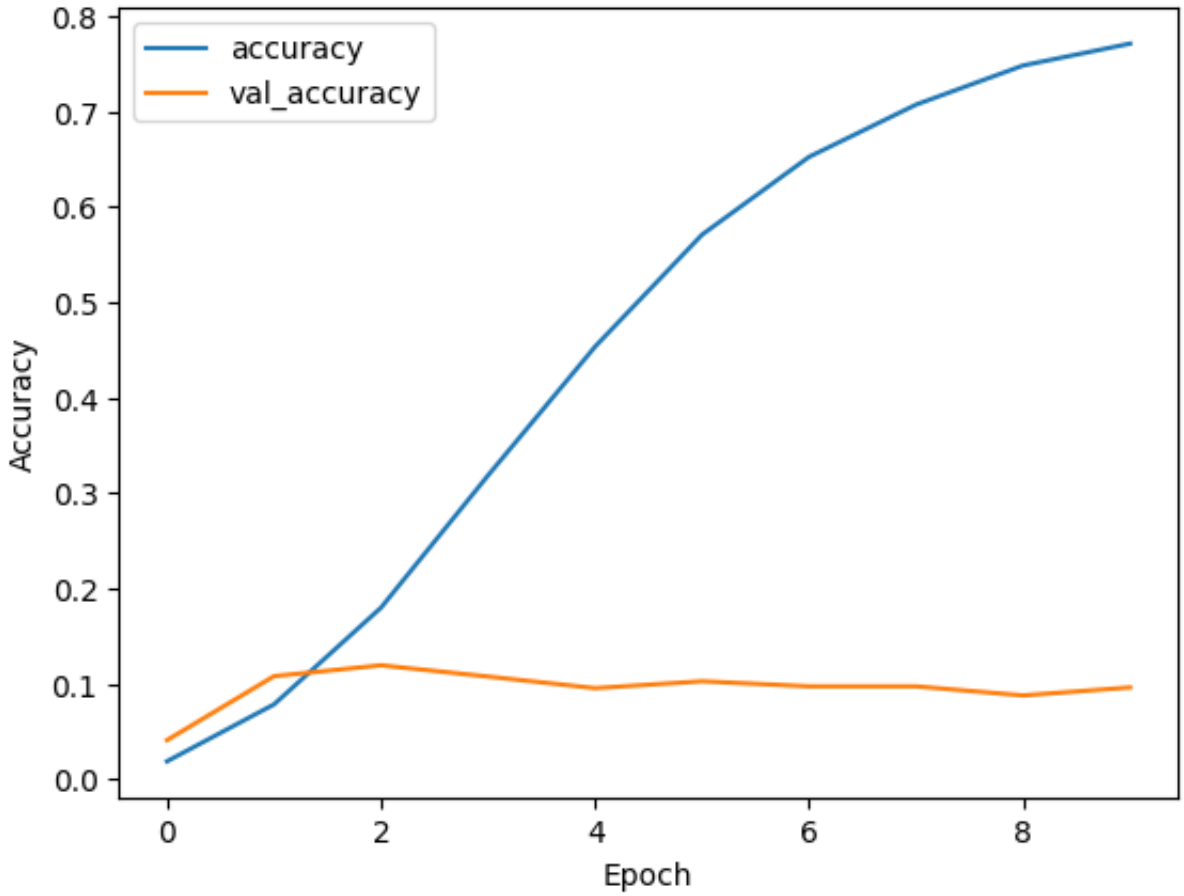
```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 224, 224, 6)       456

 max_pooling2d (MaxPooling2  (None, 112, 112, 6)       0
 D)

 conv2d_1 (Conv2D)           (None, 108, 108, 16)      2416

 max_pooling2d_1 (MaxPoolin  (None, 54, 54, 16)        0
 g2D)

 flatten (Flatten)           (None, 46656)             0

 dense (Dense)               (None, 120)               5598840

 dense_1 (Dense)             (None, 84)                10164

 dense_2 (Dense)             (None, 525)               44625

=================================================================
Total params: 5656501 (21.58 MB)
Trainable params: 5656501 (21.58 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

```
train_log = model.fit(
    tf_train_data,
    validation_data=tf_val_data,
    epochs=10
)
```

```
Epoch 1/10
2645/2645 [==============================] - 1017s 384ms/step - loss: 5.8777 -
Epoch 2/10
2645/2645 [==============================] - 993s 375ms/step - loss: 4.9527 -
Epoch 3/10
2645/2645 [==============================] - 989s 374ms/step - loss: 4.0219 -
Epoch 4/10
2645/2645 [==============================] - 988s 373ms/step - loss: 3.0594 -
Epoch 5/10
2645/2645 [==============================] - 991s 374ms/step - loss: 2.2894 -
Epoch 6/10
2645/2645 [==============================] - 990s 374ms/step - loss: 1.7252 -
Epoch 7/10
2645/2645 [==============================] - 995s 376ms/step - loss: 1.3594 -
Epoch 8/10
2645/2645 [==============================] - 987s 373ms/step - loss: 1.1260 -
Epoch 9/10
2645/2645 [==============================] - 990s 374ms/step - loss: 0.9628 -
Epoch 10/10
2645/2645 [==============================] - 983s 371ms/step - loss: 0.8628 -
```

```
plt.plot(train_log.history['accuracy'], label='accuracy')
plt.plot(train_log.history['val_accuracy'], label = 'val_accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

print('Training accuracy: %f' % train_log.history['accuracy'][-1])
print('Validation accuracy: %f' % train_log.history['val_accuracy'][-1])
```

```
Training accuracy: 0.770710
Validation accuracy: 0.096000
```

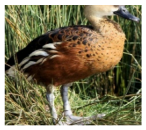



```
class_labels = df_training['labels']  # Assuming df_training contains class label

test1_dataset_iter = iter(test_dataset.take(1))

images, labels = next(test1_dataset_iter)

# Make predictions
predictions = model.predict(images)
predicted_labels = np.argmax(predictions, axis=1)
```

```
num_images = len(images)
num_rows = (num_images + 3) // 4
num_cols = min(num_images, 4)

# Display the images with their true and predicted labels
plt.figure(figsize=(25, 25))
for i in range(num_images):
    plt.subplot(num_rows, num_cols, i + 1)
    plt.imshow(images[i].numpy().astype("uint8"))
    plt.title("T: " + train_dataset.class_names[labels[i]] + " P: " + str(class_l
    plt.axis("off")
plt.show()
```

```
1/1 [==============================] - 0s 371ms/step
```



```
model_1_val_result=model.evaluate(vaild_dataset)
model_1_val_result

model_1_val_result=model.evaluate(test_dataset)
model_1_val_result
```

```
83/83 [==============================] - 7s 80ms/step - loss: 12.1336 - accura
83/83 [==============================] - 7s 78ms/step - loss: 11.8216 - accura
[11.821556091308594, 0.095238097012043]
```

Machine Learning Approaches

Baseline Evaluation Setup

- Data Splits: Our data is split between train, test, and validation sets so will will be able to have an unbiased evaluation of our model's performance.
- Accuracy as primary metric: Since we are working on a classification project, accuracy will be our more important metric. Accuracy will measure how often our model correctly predicts the bird species label from the image.
- Cross-Validation: Using k-fold cross validation will allow us to test our model's performance across our subsets, helping us to avoid overfitting.

Convolutional Neural Networks

We chose to use CNN for our project because of their proven success when it comes to image data. They are able to learn spatial hierarchies of features, which makes them highly effective in image classification.

What we will do between now and project submission

- adjust CNN to improve accuracy
- implement measures display our models accuracy
- show how new model outpreforms baseline model

Experiments

Conclusion