TEAM 11 – VINYL RECORD AND BOOK CLASSIFIER

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# PROBLEM STATEMENT

With a growing collection of books and vinyl albums it is a challenge to keep track of what I have, the vintage of the item, and current value.

Alas, a solution to the problem has been found! What a better way to use my newly acquired knowledge to begin a journey along the Al deep learning path to assist me in creating an inventory of my collection.

The first step is to get the data, then train the model....



# IMAGE CLASSIFICATION OVERVIEW

### **AGENTIC AI SYSTEM**



### DOWNLOAD IMAGES

Uses the DuckDuckGo Python library to download random images of books and vinyl records.



### TRAIN THE MODEL

Designed to train and validate a deep learning model using either MobileNetV2 or ResNet50 as the base model



### PREPROCESS IMAGES

Perform a cleaning of the images using the Tenserflow and PIC libraries with actions to convert or remove, if required.



### PREDICT THE CATEGORY

The model is intended to classify images into two categories: vinyl records and books.



### CHOOSE THE PARAMETERS

A Flask application to allow the user to configure the agents and select what agents to run.



### **VIEW RESULTS**

A built-in system to view progress in real-time and visualize the results.

# KEY FEATURES

- Model Selection: The code allows users to choose between MobileNetV2 and ResNet50 as the base model.
- Custom Preprocessing Layer: A custom preprocessing layer is implemented to handle image preprocessing for both MobileNetV2 and ResNet50.GPU
- Optimization: The code is optimized for GPU usage with shared memory optimization and auto-clustering enabled.
- XLA Compilation: The code uses XLA (Accelerated Linear Algebra) compilation to optimize computations.
- K-Fold Cross-Validation: The code implements K-Fold cross-validation to evaluate the model's performance.
- Data Augmentation: The code applies data augmentation techniques to the training data.
- Model Evaluation: The code evaluates the model's performance using metrics such as accuracy, precision, and recall.



PERFORMANCE
AND
BENCHMARKING
FEATURES

LET THE AGENTS DO THE WORK!

## AUTOMATED PERFORMANCE AND BENCHMARKING

- **GPU Performance Benchmarking:** The code includes a benchmarking function to measure the performance of the GPU with different batch sizes.
- Batch Size Optimization: The code adjusts the batch size based on the GPU's performance to optimize shared memory utilization.
- Speedup Calculation: The code calculates the speedup achieved by using batch processing with different batch sizes.
- Custom Preprocessing Layer: A custom preprocessing layer to handle image preprocessing
- Global Average Pooling Layer: A global average pooling layer to reduce the spatial dimensions of the feature maps
- Dense Layers: One or more dense layers with ReLU activation and dropout
- Final Classification Layer: A final classification layer with softmax activation



# AUTOMATED PERFORMANCE AND BENCHMARKING

```
test_paths = img_paths[:100] if len(img_paths) > 100 else img_paths
print("\n=== GPU SHARED MEMORY PERFORMANCE BENCHMARK ==
                                                Use GPU to calculate best
   f"Testing with {len(test_paths)} images,
                                                 batch size to use
print("\nBenchmarking individual image processing (baseline)...")
    for path in test paths[:10]: # Limit to 10 images for individua / processing
        _ = predict_image(model, path)
individual time = (time.time() - start time) / (10 * runs)
   f"Average time per image (individual): {individual_time*1000:.2f} ms")
results['individual'] = individual time * 1000
for batch_size in batch_sizes:
   print(f"\nBenchmarking batch size {batch size}...")
    start_time = time.time()
          = predict_batch(model, test_paths, batch_size=batch_size)
   batch_time = (time.time() - start_time) / (len(test_paths) * runs)
       f"Average time per image (batch size {batch_size}): {batch_time*1000:.2f} ms")
    results[f'batch_{batch_size}'] = batch_time * 1000
    speedup = individual_time / batch_time
   print(f"Speedup with batch size {batch_size}: {speedup:.2f}x")
results[f'speedup_{batch_size}'] = speedup
 est batch size = batch sizes[0]
```

```
Cross-Validation Results:
Average Validation Loss: 0.2789
Average Validation Accuracy: 0.9164
Best model from fold 12 with validation loss: 0.1443
Training final model on all training data...
Found 226 images belonging to 2 classes.
```

Metrics from folds used to determine "best model" to use

```
fold_model = create_model(base_model_name=model,no_of_layers=layers,use_xla=use_xla)
# Setup callbacks
fold callbacks = []
early_stopping = tf.keras.callbacks.EarlyStopping(
                                                         Configuring
                                                         each fold for
   restore_best_weights=True
                                                         early stopping
fold_callbacks.append(early_stopping)
                                                         and learning
reduce lr = tf.keras.callbacks.ReduceLROnPlateau(
                                                         rate
   factor=0.5,
   patience=5.
   min 1r=1e-6.
   verbose=1
fold_callbacks.append(reduce_lr)
```

```
0s 520ms/step - accuracy: 0.8950 - loss: 0.3043 - precision: 0.8950 - recall: 0.8950
Epoch 33: val_loss did not improve from 0.33897
Epoch 33: loss=0.3371, acc=0.8792
                      15s 579ms/step - accuracy: 0.8944 - loss: 0.3055 - precision: 0.8944 - recall: 0.8944 - val_accuracy: 0.8947 - val_loss: 0.3884 - val_precision: 0.8947 - val_rec
all: 0.8947 - learning_rate: 2.5000e-05
                      05 520ms/sten - accuracy: 0 8024 - loss: 0 3996 - precision: 0 8024 - recall: 0 8024
 och 34: val_loss did not improve from 0.33897
 och 34: loss=0.3537, acc=0.8309
och 35/100
                      • 0s 521ms/step - accuracy: 0.8872 - loss: 0.3658 - precision: 0.8872 - recall: 0.8872
 och 35: ReduceLROnPlateau reducing learning rate to 1.249999968422344e-05
Epoch 35: val_loss did not improve from 0.33897
Epoch 35: loss=0.3507, acc=0.8792
                     - 16s 581ms/step - accuracy: 0.8869 - loss: 0.3652 - precision: 0.8869 - recall\ 0.8869 - val_accuracy: 0.8947 - val_loss: 0.3929 - val_precision: 0.8947 - val_rec
all: 0.8947 - learning_rate: 2.5000e-05
Fold 7 - Validation Loss: 0.3390, Validation Accuracy: 0.8947
                                                                                               ReduceLROnPlateau callback monitors validation
raining fold 8/12
                                                                                               loss and the training uses other metrics to
 und 207 images belonging to 2 classes.
 und 19 images belonging to 2 classes.
eated Layer 0 with units of 1024.
                                                                                               improve model performance and validation.
  eated Layer 2 with units of 256
 eated Layer 3 with units of 256
 eated Layer 4 with units of 1024
 eated Layer 5 with units of 512.
```

K-Fold cross-validation to evaluate the model's performance and automated assignment of units to the layers to improve the deep learning with the training set

eated Layer 6 with units of 256

eated Layer 8 with units of 1024

eated Layer 9 with units of 512.

eated Layer 10 with units of 256

eated Layer 11 with units of 256. eated Layer 12 with units of 1024

eated Layer 13 with units of 512.

eated Laver 14 with units of 256.

snet\_xla\_True

# THE FUTURE BACKLOG OF ENHANCEMENTS

# FUTURE ENHANCEMENTS

- 1. Allow user to enter a learning rate
- 2. Allow user to enter a patience value
- 3. Allow user to enter the number of training images to fetch
- 4. Create a CSV or database inventory of the predicted images

