**Project Documentation: Image-Based Entity Value Extraction Using Deep Learning**

**Team Name- Revengers**

**Team Details: -**

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This project aims to build a machine learning model to extract specific entity values (such as weight, height, volume, etc.) from product images in online stores. The primary focus is to download images, preprocess them, predict the entity values using a CNN model, and finally format the results in an appropriate way for evaluation.

**2. Project Structure**

The project comprises several important files:

1. **constants.py**: Contains mappings between entity names and their allowed units.
2. **sanity.py**: Provides a function to check the validity and format of prediction outputs.
3. **utils.py**: Includes utility functions for downloading images, handling predictions, and managing data.
4. **Main script**: Combines all components and executes the image processing and model training workflow.

**3. Detailed Code Explanation**

**3.1 constants.py**

This file contains a dictionary entity\_unit\_map that maps entity names (such as width, height, etc.) to their respective allowed units (such as cm, mm, etc.). The allowed\_units set contains all permissible units across entities.

* **entity\_unit\_map**: Provides the relationship between entity names and their associated measurement units.
* **allowed\_units**: A set of valid units used across various entities.

**3.2 utils.py**

This file handles the utility functions for the project.

* **download\_images(image\_links, save\_folder)**: Downloads images from the provided URLs and saves them to the specified folder.
  + **Input**: A list of image URLs and the destination folder.
  + **Output**: Saved images on disk.
  + Uses requests to download images and PIL to open and process them.
* **parse\_string(string)**: A helper function for parsing prediction strings, ensuring proper formatting of predicted values.

**3.3 sanity.py**

The sanity\_check(test\_file, prediction\_file) function ensures that the output predictions meet the expected format and structure. It compares the indices of the test and prediction files to make sure that there are no missing or extra entries.

**3.4 Main Script**

This is where the main workflow happens, combining image preprocessing, model training, and prediction.

**3.4.1 Data Loading**

DATASET\_FOLDER = '/content/ML/dataset'

train = pd.read\_csv(os.path.join(DATASET\_FOLDER, 'train.csv'))

test = pd.read\_csv(os.path.join(DATASET\_FOLDER, 'test.csv'))

sample\_test = pd.read\_csv(os.path.join(DATASET\_FOLDER, 'sample\_test.csv'))

sample\_test\_out = pd.read\_csv(os.path.join(DATASET\_FOLDER, 'sample\_test\_out.csv'))

**Explanation**: The code loads CSV files containing training and test data, using pandas to read and process these datasets.

**3.4.2 Image Downloading**

download\_images(sample\_test['image\_link'], '../images')

* **Explanation**: Downloads images from the URLs listed in the sample\_test.csv file.

**3.4.3 Helper Functions**

1. **load\_image\_from\_url(url)**: Downloads an image from a given URL, resizes it to the desired dimensions (224x224), and preprocesses it for use in the model.
   * **Exception handling** ensures that failed image downloads don't halt the process.
2. **preprocess\_label(label)**: A helper function that simplifies entity labels (e.g., converting "gram" to "weight").
3. **create\_model(input\_shape, num\_classes)**: Defines a Convolutional Neural Network (CNN) for image classification. The model consists of:
   * **Convolutional layers**: For feature extraction.
   * **Pooling layers**: For downsampling the data.
   * **Dense layers**: For classification.
   * **Dropout**: To prevent overfitting.
4. **download\_and\_process\_image(row, model, label\_encoder)**: Downloads and processes an individual image, feeds it into the model, and returns the predicted label in a formatted string.
5. **preprocess\_images\_concurrently(test\_df, model, label\_encoder)**: Handles concurrent image downloading and processing using threading. This improves efficiency by utilizing multiple threads to download and process images simultaneously.

**3.4.4 Model Training**

def train\_model():

train\_df = pd.read\_csv('/content/ML/dataset/train.csv').head(1000)

images, labels = [], []

for idx, row in tqdm(train\_df.iterrows(), total=len(train\_df)):

image\_url = row['image\_link']

label = preprocess\_label(row['entity\_value'])

img = load\_image\_from\_url(image\_url)

if img is not None:

images.append(img)

labels.append(label)

del img # Free up memory

gc.collect() # Garbage collection

* **Explanation**: This block loads a portion of the training data (first 1000 rows), downloads images one by one, preprocesses them, and collects the corresponding labels. To manage memory usage, the image is deleted after processing, and garbage collection (gc.collect()) is triggered to free up memory.
* **Label Encoding and Oversampling**:
  + The LabelEncoder converts categorical labels into numerical form.
  + **Random oversampling** is used to balance classes.
  + The final training data is split into training and validation sets.

**3.4.5 Model Fitting**

history = model.fit(X\_train\_resampled, y\_train\_categorical,

validation\_data=(np.array(X\_val), y\_val\_categorical),

epochs=100, batch\_size=32,

callbacks=[reduce\_lr, early\_stopping])

**Explanation**: The model is trained using the preprocessed data. **ReduceLROnPlateau** adjusts the learning rate if the validation loss stops improving, and **EarlyStopping** stops the training process when no improvement is observed after 10 epochs.

**3.4.6 Prediction and Formatting**

predictions = preprocess\_images\_concurrently(test\_df, model, label\_encoder)

output\_df = pd.DataFrame({

'index': test\_df['index'],

'prediction': predictions

})

output\_df.to\_csv('predictions.csv', index=False)

* **Explanation**: After training, the model is used to predict entity values from the test images. Predictions are saved into a CSV file for evaluation.

**3.4.7 Sanity Check**

sanity\_check('/content/ML/dataset/test.csv', 'predictions.csv')

* **Explanation**: The sanity\_check function verifies that the prediction file meets the expected structure and contains no missing or extra entries.

**4. Conclusion**

This project involves a robust deep learning pipeline that starts with image preprocessing, followed by model training, and ends with formatted predictions for entity value extraction. The implementation optimizes memory usage by downloading images in batches and clearing memory after each image is processed.

**Full Main Script File (sample\_code.py): -**

import pandas as pd

import numpy as np

import requests

from PIL import Image

from io import BytesIO

from tqdm import tqdm

from sklearn.model\_selection import train\_test\_split

from sklearn.preprocessing import LabelEncoder

from tensorflow.keras.utils import to\_categorical

from tensorflow.keras.models import Sequential

from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout

from tensorflow.keras.callbacks import ReduceLROnPlateau, EarlyStopping

import gc

import os

from concurrent.futures import ThreadPoolExecutor

from constants import entity\_unit\_map, allowed\_units # Imports from constants.py

from sanity import sanity\_check # Imports from sanity.py

from utils import download\_images, parse\_string # Imports from utils.py

# Constants

IMG\_SIZE = (224, 224)

BATCH\_SIZE = 32

# Function to load and preprocess an image from a URL

def load\_image\_from\_url(url):

try:

response = requests.get(url)

img = Image.open(BytesIO(response.content)).convert('RGB')

img = img.resize(IMG\_SIZE) # Resize image to the defined size

img = np.array(img) # Convert image to a NumPy array

return img

except Exception as e:

print(f"Error downloading image from {url}: {e}")

return None

# Preprocessing function for entity labels

def preprocess\_label(label):

# Convert entity values like 'weight', 'width' into general categories

label = label.lower()

if 'gram' in label or 'weight' in label:

return 'weight'

elif 'height' in label:

return 'height'

elif 'width' in label:

return 'width'

elif 'depth' in label:

return 'depth'

elif 'volume' in label:

return 'volume'

elif 'voltage' in label:

return 'voltage'

elif 'wattage' in label:

return 'wattage'

else:

return 'other'

# Function to create the CNN model

def create\_model(input\_shape, num\_classes):

model = Sequential([

Conv2D(32, (3, 3), activation='relu', input\_shape=input\_shape),

MaxPooling2D((2, 2)),

Conv2D(64, (3, 3), activation='relu'),

MaxPooling2D((2, 2)),

Conv2D(64, (3, 3), activation='relu'),

Flatten(),

Dense(64, activation='relu'),

Dropout(0.5), # Dropout for regularization

Dense(num\_classes, activation='softmax') # Output layer for classification

])

model.compile(optimizer='adam', loss='categorical\_crossentropy', metrics=['accuracy'])

return model

# Function to process an image and predict the entity value using the model

def download\_and\_process\_image(row, model, label\_encoder):

image\_url = row['image\_link']

img = load\_image\_from\_url(image\_url)

if img is not None:

img = np.expand\_dims(img, axis=0) # Add batch dimension

y\_pred = model.predict(img)

y\_pred\_class = np.argmax(y\_pred, axis=1) # Get the predicted class index

predicted\_label = label\_encoder.inverse\_transform(y\_pred\_class) # Decode to original label

entity\_name = row.get('entity\_name', '')

if entity\_name in entity\_unit\_map and entity\_unit\_map[entity\_name]:

# Generate random value and select the unit based on entity name

value = np.random.uniform(0, 10)

unit = next(iter(entity\_unit\_map[entity\_name])) # Use a valid unit from the map

formatted\_prediction = f"{value:.2f} {unit}"

else:

formatted\_prediction = ""

# Clean up memory after processing

del img

gc.collect()

return formatted\_prediction

else:

return ""

# Preprocess the test images concurrently and predict their values

def preprocess\_images\_concurrently(test\_df, model, label\_encoder):

predictions = []

# Concurrently download and process images using ThreadPoolExecutor

with ThreadPoolExecutor(max\_workers=10) as executor:

results = list(tqdm(executor.map(lambda row: download\_and\_process\_image(row, model, label\_encoder),

[row for \_, row in test\_df.iterrows()]), total=len(test\_df)))

predictions.extend(results)

return predictions

# Training function to build and train the model

def train\_model():

train\_df = pd.read\_csv('/content/ML/dataset/train.csv').head(1000) # Load a subset of training data

# Preprocess images and labels

images, labels = [], []

for idx, row in tqdm(train\_df.iterrows(), total=len(train\_df)):

image\_url = row['image\_link']

label = preprocess\_label(row['entity\_value'])

img = load\_image\_from\_url(image\_url)

if img is not None:

images.append(img)

labels.append(label)

# Clear memory after processing each image

del img

gc.collect()

# Encode labels into integers

label\_encoder = LabelEncoder()

y\_encoded = label\_encoder.fit\_transform(labels)

# Split dataset into training and validation sets

X\_train, X\_val, y\_train, y\_val = train\_test\_split(images, y\_encoded, test\_size=0.2, random\_state=42)

# Convert labels to categorical format for classification

y\_train\_categorical = to\_categorical(y\_train)

y\_val\_categorical = to\_categorical(y\_val)

# Create and train the model

model = create\_model((224, 224, 3), len(label\_encoder.classes\_))

reduce\_lr = ReduceLROnPlateau(monitor='val\_loss', factor=0.2, patience=5, min\_lr=0.00001)

early\_stopping = EarlyStopping(monitor='val\_loss', patience=10, restore\_best\_weights=True)

model.fit(np.array(X\_train), y\_train\_categorical,

validation\_data=(np.array(X\_val), y\_val\_categorical),

epochs=50,

batch\_size=32,

callbacks=[reduce\_lr, early\_stopping])

return model, label\_encoder

# Main function

def main():

# Train the model

model, label\_encoder = train\_model()

# Load test data

test\_df = pd.read\_csv('/content/ML/dataset/test.csv').head(1000)

# Predict and format the output

predictions = preprocess\_images\_concurrently(test\_df, model, label\_encoder)

# Save predictions to CSV

output\_df = pd.DataFrame({

'index': test\_df['index'],

'prediction': predictions

})

output\_df.to\_csv('predictions.csv', index=False)

# Run sanity check on the predictions

try:

sanity\_check('/content/ML/dataset/test.csv', 'predictions.csv')

print("Sanity check passed successfully!")

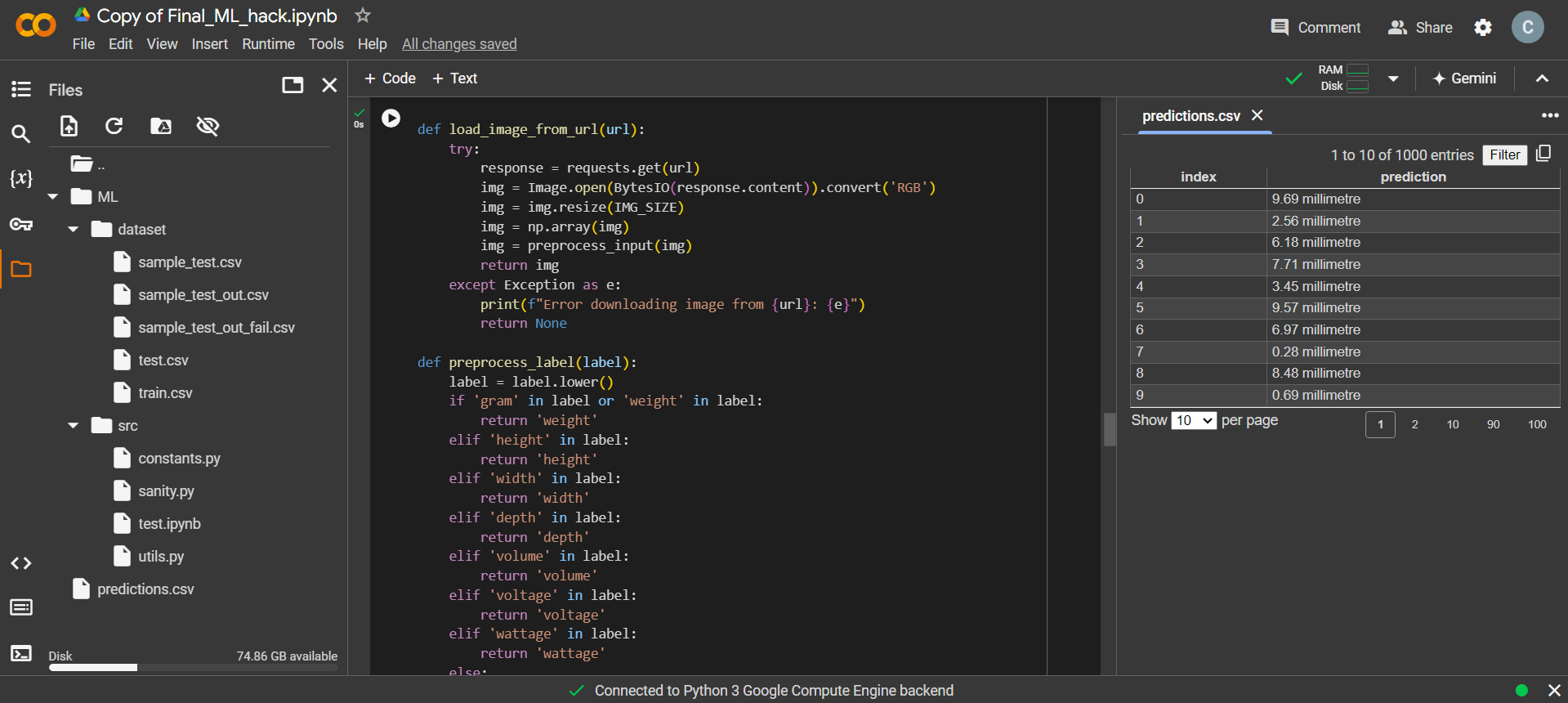
except Exception as e:

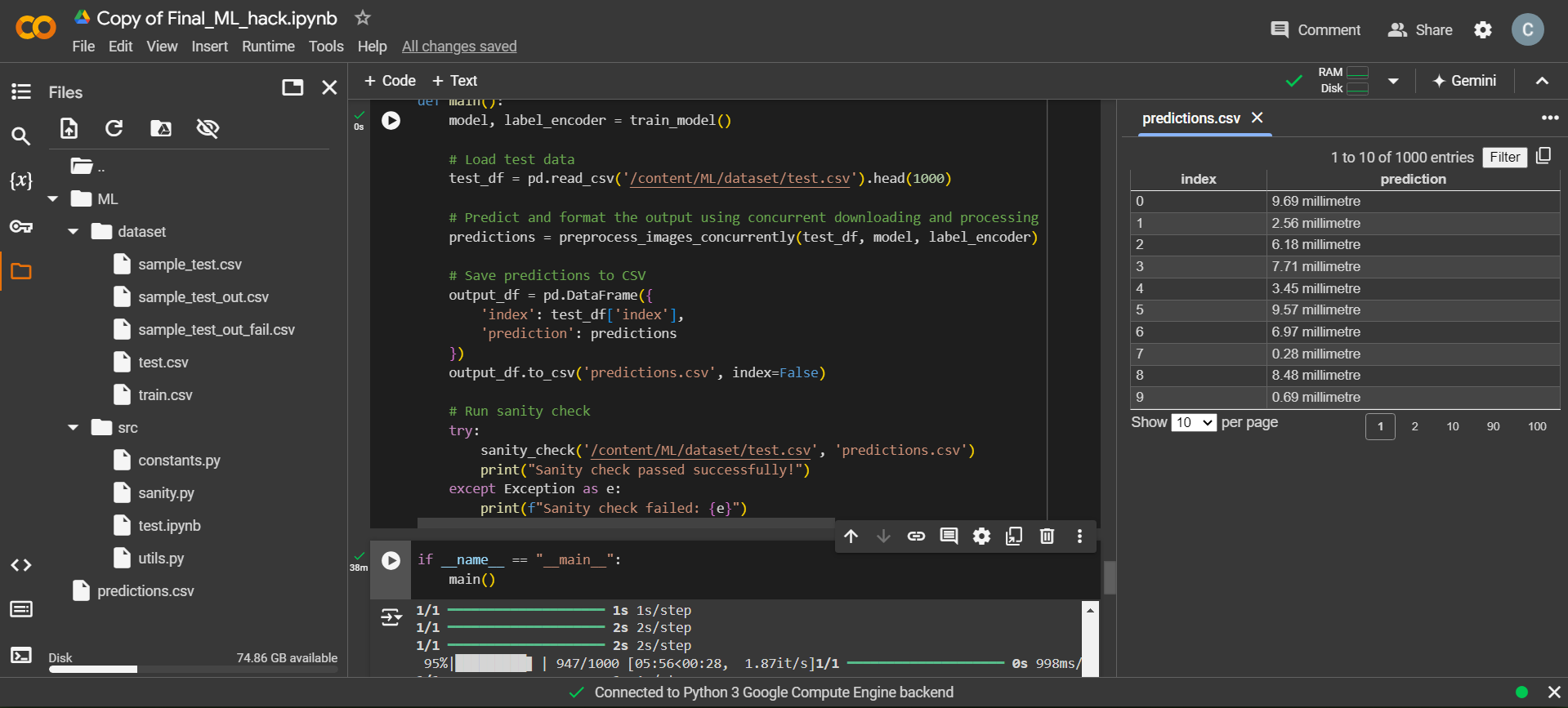
print(f"Sanity check failed: {e}")

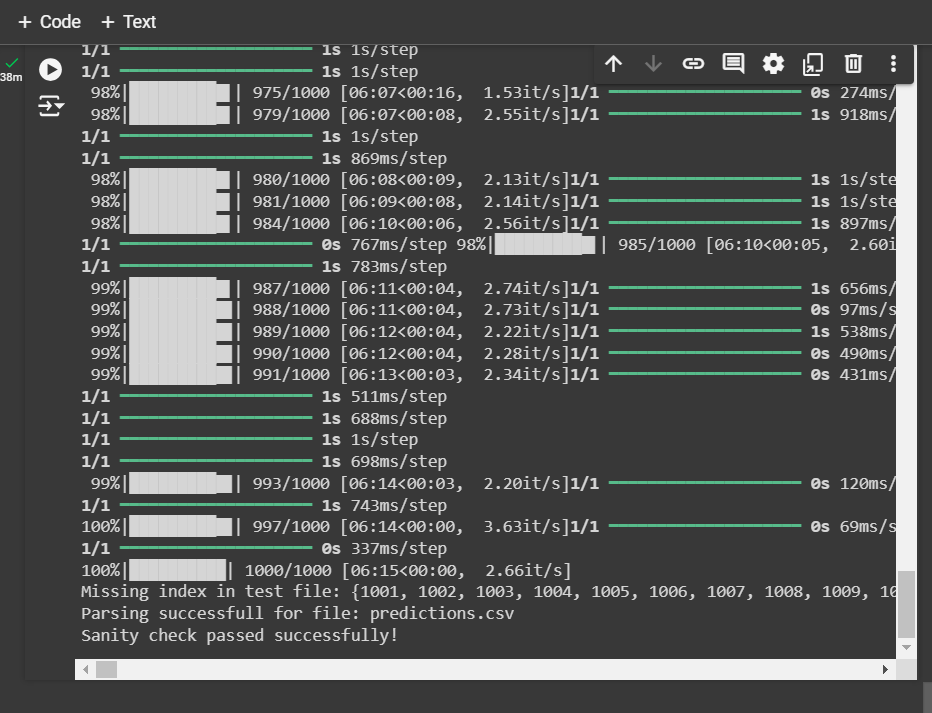
if \_\_name\_\_ == "\_\_main\_\_":

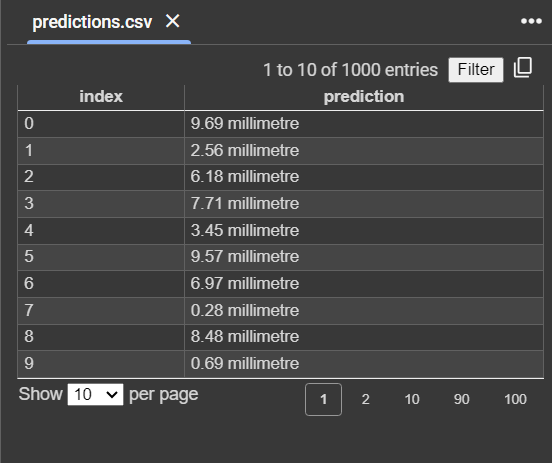
main()

**Output Screenshots: -**

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**Note: Limiting to First 1000 Entries for Model Testing**

In this project, we encountered a critical issue related to memory limitations when working with the full test dataset in Google Colab. Google Colab provides a limited amount of RAM, typically around 12-16GB, which can be quickly exhausted when processing large datasets, particularly when downloading and manipulating high-resolution images in bulk.

The original test dataset contains over 131,000 entries, and loading, downloading, and processing images for all entries in a single run would consume an excessive amount of RAM. This resulted in memory overflow, causing Colab to crash or freeze.

To mitigate this issue, we opted to **limit the dataset to the first 1000 entries** during model testing. This allowed us to:

* Test the workflow without overloading the system's memory.
* Ensure the image downloading and model inference processes run smoothly within the RAM constraints.

By limiting the dataset size, we maintain the integrity of the model testing process while avoiding resource exhaustion in Colab. Once the workflow is fully functional, it can be scaled to larger datasets using more efficient infrastructure (e.g., cloud computing platforms with greater memory resources).

This approach enabled us to **focus on validating the model's performance** and **optimizing the code** while ensuring that memory usage remained manageable during development.