

Data Collection and Preprocessing

Date	03 July 2024
Team ID	SWTID1720085445
Project Name	Hydration Essentials: Classifying Water Bottle Images
Maximum Marks	6 Marks

Preprocessing Template

The images will be preprocessed by resizing, normalizing, augmenting, denoising, adjusting contrast, detecting edges, converting color space, cropping, batch normalizing, and whitening data. These steps will enhance data quality, promote model generalization, and improve convergence during neural network training, ensuring robust and efficient performance across various computer vision tasks.

Section	Description
Data Overview	The project "Hydration Essentials: Classification of Water Bottle Levels" aims to develop a deep learning model that can classify the level of water in a bottle using images. This application could be useful in various scenarios, such as monitoring hydration levels in healthcare settings, smart home devices, or fitness applications
Resizing	<ul style="list-style-type: none"> • Uniform Input Size: <ul style="list-style-type: none"> • Neural networks require a consistent input size for processing. Resizing ensures that all images fed into the network are of the same dimensions. • Memory and Computational Efficiency: <ul style="list-style-type: none"> • Standardizing image sizes can help manage memory usage and computational load, making the training process more efficient. • Improving Convergence:

	<ul style="list-style-type: none"> • Having uniform image sizes can help the model converge faster during training by reducing variability in the input data
Normalization	<ul style="list-style-type: none"> • Improving Convergence: <ul style="list-style-type: none"> • Neural networks train faster and more reliably when the input data is normalized. This is because normalization ensures that the gradient descent optimization process is more stable and converges more quickly. • Reducing Internal Covariate Shift: <ul style="list-style-type: none"> • By normalizing the input data, the distribution of the input values becomes more consistent, reducing the shift in data distribution during training. This helps in maintaining the stability of the learning process. • Equalizing the Influence of Features: <ul style="list-style-type: none"> • Normalization ensures that all features contribute equally to the model's predictions, preventing any single feature from dominating due to its scale.
Data Augmentation	<ul style="list-style-type: none"> • Increasing Dataset Size: <ul style="list-style-type: none"> • Augmentation generates additional training examples by creating variations of existing images, thereby providing more diverse data for the model to learn from. • Improving Generalization: <ul style="list-style-type: none"> • By exposing the model to a wider range of variations (such as rotations, translations, flips, etc.), data augmentation helps the model generalize better to unseen data and variations in real-world scenarios. • Reducing Overfitting: <ul style="list-style-type: none"> • Augmentation introduces randomness and variability into the training data, which helps prevent the model from memorizing specific details of the training set and thus reduces overfitting.

Denoising	<ul style="list-style-type: none"> • Enhancing Image Quality: <ul style="list-style-type: none"> • By reducing noise, denoising techniques improve the clarity and sharpness of images, making them more suitable for visual inspection and analysis. • Improving Performance: <ul style="list-style-type: none"> • Cleaner images lead to more accurate results in tasks such as image classification, object detection, and segmentation, where noise can interfere with feature extraction and pattern recognition. • Preprocessing for Downstream Tasks: <ul style="list-style-type: none"> • Denoising is often a crucial preprocessing step before applying other techniques such as feature extraction, registration, or image enhancement.
Edge Detection	<ul style="list-style-type: none"> • Feature Extraction: <ul style="list-style-type: none"> • Edges highlight significant changes in intensity, which are useful for identifying object boundaries and shapes in images. • Image Segmentation: <ul style="list-style-type: none"> • Edge information can be used to partition an image into meaningful regions or segments based on the boundaries detected. • Object Detection and Recognition: <ul style="list-style-type: none"> • Detecting edges helps in identifying objects by their shapes and distinguishing them from the background.
Data Preprocessing Code Screenshots	

Loading Data	<pre>dataset_path = r"C:\Users\bhanu\OneDrive\Desktop\archive" images, labels = load_images_from_folder(dataset_path)</pre> <p>Python</p> <p>Loading images from folder: C:\Users\bhanu\OneDrive\Desktop\archive\Full Water level C:\ProgramData\anaconda3\lib\site-packages\PIL\Image.py:981: UserWarning: Palette images with Transparency expressed in bytes should be converted to RGBA images warnings.warn(Loading images from folder: C:\Users\bhanu\OneDrive\Desktop\archive\Half water level Loading images from folder: C:\Users\bhanu\OneDrive\Desktop\archive\Overflowing Total images loaded: 486</p>
Resizing	<pre>resize_and_rescale = tf.keras.Sequential([layers.experimental.preprocessing.Resizing(IMAGE_SIZE, IMAGE_SIZE), layers.experimental.preprocessing.Rescaling(1./255),])</pre>
Normalization	<pre>if images.size == 0 or labels.size == 0: raise ValueError("No images or labels found. Please check the folder structure and paths.") print(f"Shape of images array: {images.shape}") print(f"Number of labels: {len(labels)}") print(f"Example labels: {labels[:10]}")</pre> <p>Shape of images array: (486, 64, 64, 3) Number of labels: 486 Example labels: ['Full Water level' 'Full Water level' 'Full Water level' 'Full Water level' 'Full Water level' 'Full Water level' 'Full Water level' 'Full Water level' 'Full Water level' 'Full Water level']</p>
Data Augmentation	<pre>data_augmentation = tf.keras.Sequential([layers.experimental.preprocessing.RandomFlip("horizontal_and_vertical"), layers.experimental.preprocessing.RandomRotation(0.2),])</pre>

Denoising

```
import cv2

# Load a noisy image
noisy_image = cv2.imread('noisy_image.jpg', cv2.IMREAD_GRAYSCALE)

# Apply Gaussian Blur for denoising
denoised_image = cv2.GaussianBlur(noisy_image, (5, 5), 0)

# Display the results
cv2.imshow('Noisy Image', noisy_image)
cv2.imshow('Denoised Image', denoised_image)
cv2.waitKey(0)
cv2.destroyAllWindows()
```

Edge Detection

```
# Apply Gaussian blur to reduce noise
blurred = cv2.GaussianBlur(image, (3, 3), 0)

# Apply Canny edge detection
edges = cv2.Canny(blurred, 30, 150)

# Display the results
cv2.imshow('Original Image', image)
cv2.imshow('Canny Edges', edges)
cv2.waitKey(0)
cv2.destroyAllWindows()
```