A Picture is worth a Thousand Words:

Detecting words using OCR

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Author Note

This project, "*A Picture is Worth a Thousand Words: Detecting Words Using OCR*," was developed for AAI-521: Applied Computer Vision for AI at the University of San Diego. Team members include Outhai Xayavongsa (Team Leader), Jay Patel (Team Member), and Daniel Shifrin (Team Member). The project showcases a robust OCR pipeline using EasyOCR and TrOCR to extract and interpret text from diverse image datasets. The project code can be accessed at https://github.com/oxayavongsa/aai-521-computer-vision-final.

Abstract

This study explores the development and evaluation of Optical Character Recognition (OCR) pipelines using EasyOCR and TrOCR for text extraction from diverse and challenging image datasets. The TextOCR dataset, comprising over 900,000 word-level annotations, was used to train and evaluate these models (Singh et al., 2021). Preprocessing techniques such as grayscale conversion, noise reduction, binarization, and deskewing were applied to ensure consistent input quality. EasyOCR, a lightweight tool, excelled in handling simpler layouts with its rule-based methods, while TrOCR, leveraging a transformer-based VisionEncoderDecoder architecture, outperformed EasyOCR in recognizing distorted layouts, multilingual content, and text in noisy environments. Performance evaluation metrics, including Word Error Rate (WER) and Character Error Rate (CER), highlighted TrOCR's superior accuracy (WER: 1.00%, CER: 0.99%) compared to EasyOCR (WER: 3.10%, CER: 3.87%). The findings underscore the importance of advanced preprocessing techniques, robust model architectures, and ground truth validation in building scalable and efficient OCR systems, suitable for applications like document digitization, accessibility, and automated data processing.

Keywords: Optical Character Recognition (OCR), EasyOCR, TrOCR, TextOCR Dataset, Preprocessing Techniques, Word Error Rate (WER), Character Error Rate (CER), Transformer Models, VisionEncoderDecoder, Text Extraction, Ground Truth, Image Preprocessing.

Extracting meaningful information from images is a critical task in today's digital landscape, with applications like document digitization and automated data entry driving the demand for robust Optical Character Recognition (OCR) systems. OCR technology enables machines to interpret textual content from diverse image formats, making it a cornerstone for processing unstructured data (Chaudhuri et al., 2016). Our project, *"A Picture is Worth a Thousand Words: Detecting Words Using OCR,"* focuses on leveraging advanced OCR tools—EasyOCR and TrOCR—to create a robust text-recognition pipeline. Utilizing the TextOCR dataset, the project aims to address diverse image qualities, layouts, and complexities to achieve reliable and efficient text extraction.

Addressing the limitations of existing OCR systems is critical, as they often struggle with poor resolution, distorted or curved text, multilingual content, and environmental noise such as shadows or cluttered backgrounds. These challenges result in inconsistent performance across diverse datasets. The goal is to develop a robust and scalable OCR pipeline by integrating EasyOCR's efficiency with TrOCR's transformer-based accuracy. By leveraging advanced preprocessing techniques, iterative validation, and metrics like Word Error Rate (WER) and Character Error Rate (CER), the system is designed to extract text reliably from complex and noisy image datasets, enabling applications like large-scale digitization and automated data processing.

Data Cleaning and Preprocessing

To prepare the dataset we applied both filtering and preprocessing techniques to structure the data most optimally. Specifically, our original data set started with 25,144 images and filtered to 19,851. We applied image quality checks based on brightness, contrast, and sharpness. For brightness, we set our value to 50 using a scale of 0-255 scale to filter out images that are too

dark. Secondly, we checked the contrast threshold to measure differences between the lightest and darkest areas of the image with a threshold set to 20 indicating text and background that would be similar making the model difficult to pick up text. Last, we removed motion blur, nonfood, or low-quality images for the sharpness threshold by setting the threshold to 100.

Following this initial filtering, preprocessing techniques were applied to prepare the images for input into the OCR models. These techniques included grayscale conversion to reduce color-related noise and focus on text features, noise reduction through image smoothing, deskewing to correct any text misalignment, and binarization to enhance the distinction between text and background. These preprocessing steps were implemented to have input data that met the quality standards for the models to perform optimally for text identification and extraction. The data cleaning and preprocessing pipeline were needed to address the challenges posed by the diverse TextOCR dataset with the variability of the image quality that introduced text orientation, and image complexity. This is an important role, to make sure the input that feeds the model has a strong base image structure to enable the models to be reliable and accurate as the input directly impacts the performance of the models.

Exploratory Data Analysis (EDA) and Feature Analysis

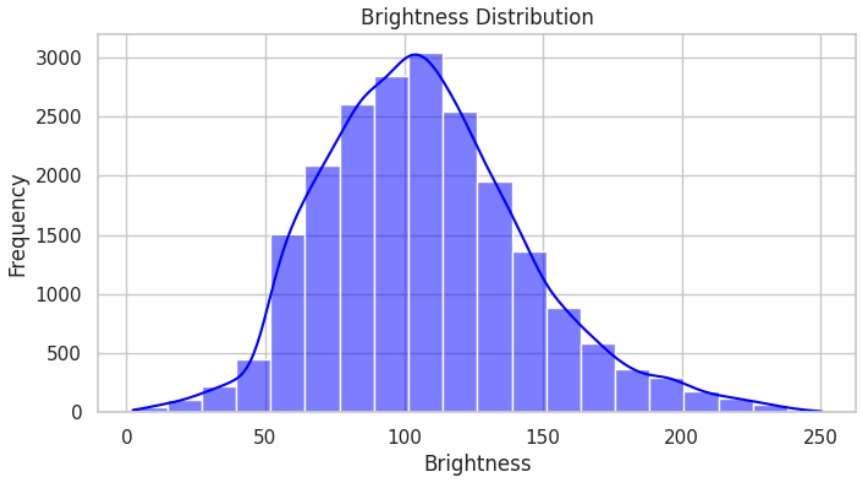
The TextOCR dataset provides a rich and diverse collection of images annotated with textual data, serving as a critical resource for training and evaluating OCR models. To optimize modeling performance, an Exploratory Data Analysis (EDA) was conducted to understand dataset characteristics and identify potential challenges. The dataset includes approximately 1 million word annotations stored in JSON format, detailing text location, shape, and content. These annotations are crucial for generating ground truth data, which is essential for model training and validation. The dataset's real-world diversity presents significant challenges, such as

varied text orientations (horizontal, vertical, and curved), multilingual content, and inconsistent image quality, all of which test OCR systems' ability to generalize effectively.

The EDA highlighted several key patterns. Most words are fewer than ten characters, reflected in a positively skewed text length distribution. Text orientation varies widely, underscoring the need for models that can handle arbitrary alignments. While the dataset predominantly contains English text, the inclusion of multilingual content offers an opportunity to assess OCR systems' cross-lingual performance. Image quality variability is evident in the brightness distribution (Figure 1). The brightness distribution reveals a concentration within a specific range, but outliers with excessively dark or overly bright areas indicate the need for normalization to enhance text clarity.

Figure 1

Brightness Distribution

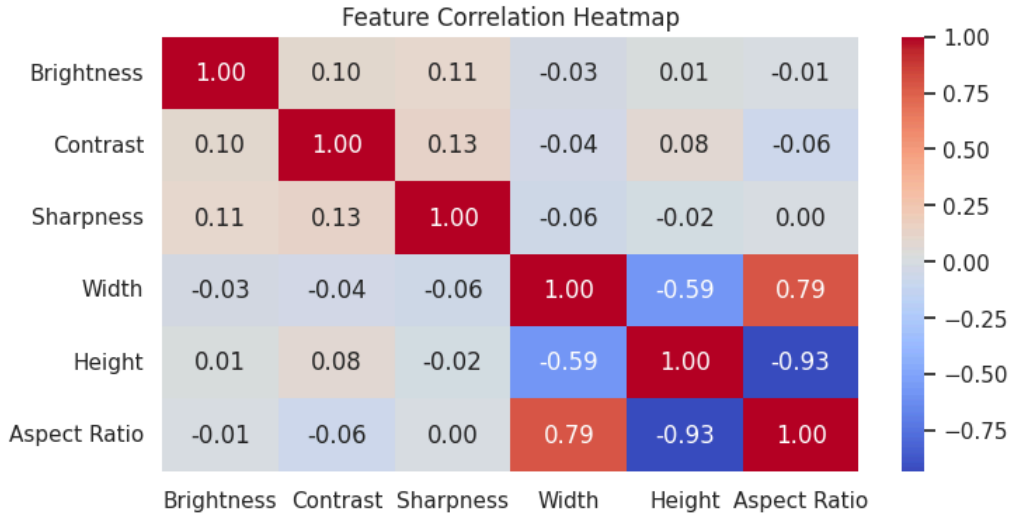


For feature analysis, TrOCR utilizes a transformer-based VisionEncoderDecoder model that leverages a self-attention mechanism for advanced feature extraction, enabling it to

effectively interpret diverse and complex text patterns. This method, illustrated by the Feature Correlation Heatmap (Figure 2), highlights the interactions between brightness, sharpness, and image dimensions, emphasizing their influence on OCR performance. In contrast, EasyOCR relies on heuristic-based pre-trained pipelines, offering simplicity and efficiency but needing to catch up in handling intricate scenarios. While EasyOCR is well-suited for straightforward text layouts, TrOCR's deep learning architecture demonstrates superior adaptability to varied and challenging datasets.

Figure 2

Feature Correlation Heatmap



Figures like the brightness and sharpness distributions and the annotated examples of bounding boxes (Figure 3) further illustrate the dataset's complexity. These insights highlight the importance of robust preprocessing and model design to address the challenges posed by this real-world dataset effectively.

Figure 3

Annotated Examples of Bounding Boxes after Ground Truth Merging

Modeling Methods and Algorithms

The modeling methods combined EasyOCR's simplicity with TrOCR's robustness to handle diverse image datasets. EasyOCR, a lightweight tool, processed text efficiently using its *readtext* function to detect regions, extract text, and compile results. Configured with a language setting, *easyocr.Reader(["en"])*, it provided quick and effective text recognition for straightforward layouts. However, its reliance on rule-based methods limited its accuracy with noisy data, distorted text, and complex layouts.

TrOCR provided an advanced solution with its VisionEncoderDecoder transformer architecture, effectively handling complex text orientations, fonts, and backgrounds.

Preprocessed images were converted to RGB and processed by the TrOCR processor to extract pixel values, which were input into the VisionEncoderDecoder model. The model generated predictions that were decoded into human-readable text using TrOCR's tokenizer, achieving significantly lower WER and CER compared to EasyOCR.

Alternative methods like CRNN, YOLO-based text detection, Keras OCR, PaddleOCR, and Tesseract were explored but excluded due to issues like task misalignment, dependency conflicts, or integration challenges. EasyOCR and TrOCR emerged as the best solutions, with EasyOCR offering simplicity and speed, while TrOCR excelled in performance and handling complexity.

Model Training, Validation, and Metrics

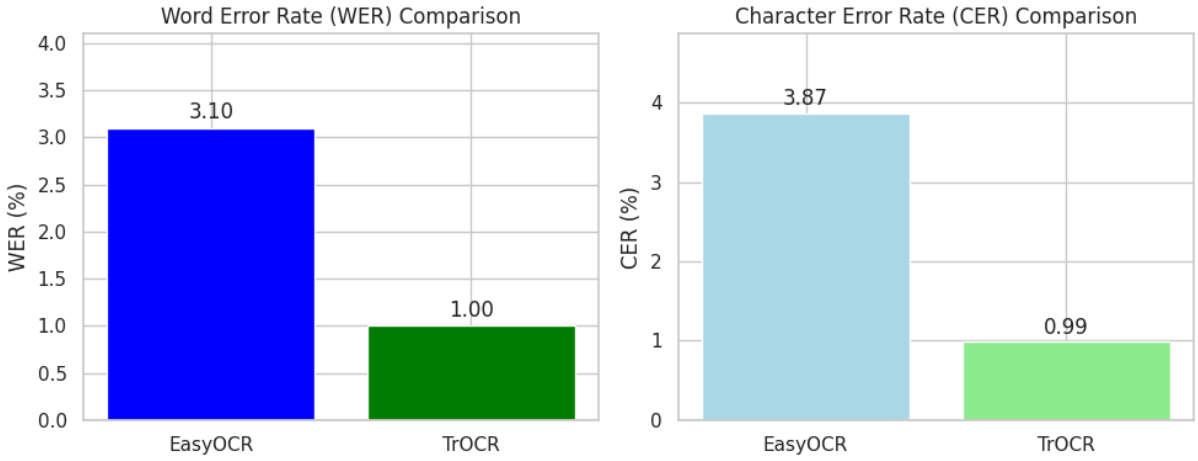
EasyOCR, pre-trained and rule-based, required no additional training and directly extracted text using its *readtext* function. In contrast, TrOCR utilized a deep-learning approach, processing RGB images through a VisionEncoderDecoder transformer where the encoder captured visual features, and the decoder predicted text sequences based on ground truth. Ground truth also played a pivotal role in validating both models, allowing reliable performance evaluation and debugging of bounding box alignment and text errors. Training with a batch size of 16 over three epochs, optimized by AdamW and a learning rate scheduler, ensured stability and efficiency using Hugging Face's *Seq2SeqTrainer*.

Validation assessed both models on separate datasets to ensure generalization and prevent overfitting. EasyOCR processed validation images with its readtext function, comparing outputs to ground truth. TrOCR generated and decoded text predictions, also compared to ground truth. Metrics like WER and CER measured accuracy after each epoch, while visual validation highlighted issues with bounding boxes, text orientation, and noise for refinement.

WER and CER, calculated using the Jiwer library, provided a quantitative assessment of the models' word and character recognition accuracy by comparing their outputs with ground truth text. TrOCR outperformed EasyOCR with a WER of 1.00% and CER of 0.99%, compared to EasyOCR's WER of 3.10% and CER of 3.87% (Figure 4). TrOCR demonstrated superior capabilities in managing complex layouts and text distortions, leveraging its transformer-based architecture for enhanced accuracy. EasyOCR, while less effective in challenging scenarios, offered faster inference, making it suitable for simpler tasks. These results highlight the complementary strengths of the two models in addressing varied OCR needs.

Figure 4

Word Error Rate (WER) versus Character Error Rate (CER) for EasyOCR and TrOCR Models.



Results and Analysis, Findings, Discussion, and Conclusion

The results demonstrated that TrOCR significantly outperformed EasyOCR in accuracy, as shown in Figure 4. TrOCR achieved a Word Error Rate (WER) of 1.00% and a Character Error Rate (CER) of 0.99%, compared to EasyOCR's WER of 3.10% and CER of 3.87%. These

metrics were computed using the Jiwer library, which compared the models' outputs with high-quality ground truth annotations. TrOCR's transformer-based VisionEncoderDecoder architecture enabled it to handle complex layouts, curved text, and multilingual content effectively. In contrast, EasyOCR, a pre-trained and rule-based model, demonstrated faster inference but was less robust in scenarios with distorted or noisy text. This distinction highlights the architectural advantages of TrOCR for datasets with intricate text arrangements. EasyOCR struggled with text containing detailed fonts and curved layouts, leading to inaccuracies such as misinterpreting "TRADITION LIBERATED" as "TTaDITIOI} LIBeraten." This visual example (Figure 5) highlights EasyOCR's limitations when faced with more challenging text scenarios.

Figure 5

EasyOCR Prediction on a Curved Text Label Demonstrating Recognition Challenges

The preprocessing pipeline also played a critical role in improving OCR accuracy. Techniques such as grayscale conversion, Gaussian blur for noise reduction, adaptive binarization, and deskewing ensured high-quality inputs for both models, reducing potential error

rates early in the process. These steps addressed text misalignment and noise issues that could otherwise hinder OCR performance. Despite these improvements, both models exhibited limitations when processing images with extremely low light or resolution, which contributed to residual error rates, even in TrOCR's outputs.

In conclusion, EasyOCR and TrOCR offer complementary strengths. EasyOCR's lightweight, resource-efficient design makes it suitable for tasks involving simple, well-structured text and scenarios requiring quick inference. TrOCR, leveraging its deep-learning framework, excels in handling complex, noisy, or multilingual datasets. TrOCR was the optimal choice, as its architecture and preprocessing integration provided superior accuracy for the dataset's challenging layouts and text conditions. Future work could focus on addressing low-light and low-resolution challenges through enhanced preprocessing or additional model fine-tuning to further improve OCR performance.

References

Chaudhuri, A., Mandaviya, K., Badelia, P., & Ghosh, S. K. (2016). Optical character recognition systems for different languages with soft computing. In *Optical Character Recognition Systems* (pp. 9–41). Springer. https://doi.org/10.1007/978-3-319-50252-6_2

Singh, A., Pang, G., Toh, M., Huang, J., Galuba, W., & Hassner, T. (2021). *TextOCR - Text Extraction from Images Dataset*. Retrieved from https://www.kaggle.com/datasets/robikscube/textocr-text-extraction-from-images-dataset

UBIAI. (2022, November 23). *Top open-source OCR programs*. Retrieved from https://ubiai.tools/top-open-source-ocr-programs/

Open in Colab

Install Libraries

In [6]:

```
# Install Libraries (Install if needed)
# !apt-get install -y tesseract-ocr
# !pip install pytesseract
# !pip install torch torchvision transformers tqdm
# !pip install tqdm
# !pip install tensorflow matplotlib opencv-python-headless
# !pip install easyocr
# !pip install pyarrow
# !pip install fastparquet
# !pip install datasets
# !pip install evaluate
# !pip install jiwer
```

Import Libraries

In [18]:

```
# --- SYSTEM AND FILE HANDLING ---
import os
import random
from zipfile import ZipFile
from shutil import copyfile

# --- DATA MANIPULATION ---
import json
import numpy as np
import pandas as pd

# --- METRICS AND ERROR MEASUREMENTS ---
from jiwer import cer, wer

# --- IMAGE PROCESSING ---
import cv2
from PIL import Image, ImageStat
import pytesseract

# --- DATA VISUALIZATION ---
import matplotlib.pyplot as plt
import matplotlib.patches as patches
import seaborn as sns
from tqdm import tqdm

# --- DEEP LEARNING LIBRARIES ---
import torch
from torch.utils.data import DataLoader
from torchvision.transforms import Compose, Resize, ToTensor

# --- TRANSFORMERS AND OCR MODELS ---
from transformers import (
    TrOCRProcessor,
    VisionEncoderDecoderModel,
    Seq2SeqTrainer,
```

```
    Seq2SeqTrainingArguments,
    AdamW,
    get_scheduler,
)
from datasets import Dataset, DatasetDict
import evaluate  # Correctly replace load_metric

# --- OCR LIBRARIES ---
import easyocr

# --- WARNINGS SUPPRESSION ---
import warnings
import logging
from transformers import logging as hf_logging

# Set up logging to suppress unnecessary warnings and info messages
warnings.filterwarnings("ignore")  # Suppress all Python warnings
hf_logging.set_verbosity_error()  # Suppress specific transformers warnings
logging.getLogger("transformers").setLevel(logging.ERROR)  # Set logging level f
```

Collect and Load Data

In [8]:

```
# --- MOUNT GOOGLE DRIVE ---
from google.colab import drive

print("Mounting Google Drive...")
drive.mount('/content/drive')

google_drive_path = "/content/drive/My Drive/Colab Notebooks/AAI-521-Computer Vi
print("Available files:", os.listdir(google_drive_path))
```

```
Mounting Google Drive...
Mounted at /content/drive
Available files: ['TextOCR Dataset.zip', 'TextOCR Dataset.zip (Unzipped Files)',
'TextOCR_test_Images_filtered.zip', 'preprocessed_images.zip', 'output_images.zi
p', 'Model_TcOCR_Final_Version2.ipynb']
```

Understanding Data

In [11]:

```
# Correct path to the dataset
google_drive_zip_path = "/content/drive/My Drive/Colab Notebooks/AAI-521-Compute
unzipped_folder = "/content/unzipped_dataset"


def unzip_dataset(zip_path, extract_to):
    if os.path.exists(zip_path):
        print(f"Extracting dataset from {zip_path}...")

        # Open the zip file
        with ZipFile(zip_path, 'r') as zip_ref:
            # Get the list of files to extract
            file_list = zip_ref.namelist()

            # Create a progress bar for extraction
```

```
            for file in tqdm(file_list, desc="Extracting", unit="file"):
                zip_ref.extract(file, extract_to)

        print(f"Dataset extracted to {extract_to}")
    else:
        raise FileNotFoundError(f"Zip file not found at {zip_path}")


# Unzip the dataset with progress bar
unzip_dataset(google_drive_zip_path, unzipped_folder)

# List the unzipped dataset
print("\n----- Top Level Files -----")
!ls /content/unzipped_dataset

# Optionally, find all directories within the unzipped dataset
print("\n----- Dataset Directory -----")
!find /content/unzipped_dataset -type d
```

```
Extracting dataset from /content/drive/My Drive/Colab Notebooks/AAI-521-Computer V
ision Dataset/TextOCR Dataset.zip...
Extracting: 100%|██████████| 25124/25124 [02:13<00:00, 188.44file/s]
Dataset extracted to /content/unzipped_dataset

----- Top Level Files -----
annot.csv  annot.parquet  img.csv  img.parquet  TextOCR_0.1_train.json  train_val_
images
----- Dataset Directory -----
/content/unzipped_dataset
/content/unzipped_dataset/train_val_images
/content/unzipped_dataset/train_val_images/train_images
```

In [57]:

```
# ~~~~~ Top Level Files ~~~~~ Data Sample
# Correct paths to dataset files and folders
base_path = "/content/unzipped_dataset"
csv_files = [os.path.join(base_path, "annot.csv"), os.path.join(base_path, "img.
parquet_files = [os.path.join(base_path, "annot.parquet"), os.path.join(base_pat
json_file = os.path.join(base_path, "TextOCR_0.1_train.json")
image_folder = os.path.join(base_path, "train_val_images/train_images")

# Prepare a dictionary to store file samples for visualization
file_samples = {}

# Load and collect CSV file samples
for file in csv_files:
    try:
        df = pd.read_csv(file)
        file_samples[file] = df.head()  # Collect first 5 rows
    except Exception as e:
        file_samples[file] = pd.DataFrame({"Error": [str(e)]})  # Collect error

# Load and collect Parquet file samples
for file in parquet_files:
    try:
        df = pd.read_parquet(file)
        file_samples[file] = df.head()  # Collect first 5 rows
    except Exception as e:
        file_samples[file] = pd.DataFrame({"Error": [str(e)]})  # Collect error
```

```python
# Load and collect JSON file samples
try:
    with open(json_file, 'r') as f:
        data = json.load(f)
        # Convert first 5 keys and values to DataFrame
        json_sample = {k: data[k] for k in list(data.keys())[:5]}
        file_samples[json_file] = pd.DataFrame.from_dict(json_sample, orient='in
except Exception as e:
    file_samples[json_file] = pd.DataFrame({"Error": [str(e)]})

# Load and collect image folder sample
try:
    image_sample = os.listdir(image_folder)[:5]
    file_samples[image_folder] = pd.DataFrame({"Images": image_sample})  # Conve
except Exception as e:
    file_samples[image_folder] = pd.DataFrame({"Error": [str(e)]})  # Collect er

# Display DataFrame contents
for file_path, sample_df in file_samples.items():
    print(f"--- Sample from {file_path} ---")
    print(sample_df)
```

```
--- Sample from /content/unzipped_dataset/annot.csv ---
   Unnamed: 0                id          image_id  \
0           0  a4ea732cd3d5948a_1  a4ea732cd3d5948a
1           1  a4ea732cd3d5948a_2  a4ea732cd3d5948a
2           2  a4ea732cd3d5948a_3  a4ea732cd3d5948a
3           3  a4ea732cd3d5948a_4  a4ea732cd3d5948a
4           4  a4ea732cd3d5948a_5  a4ea732cd3d5948a

                          bbox  utf8_string  \
0   [525.83, 3.4, 197.64, 33.94]  Performance
1  [534.67, 64.68, 91.22, 38.19]        Sport
2  [626.95, 63.62, 96.52, 31.82]        Watch
3  [577.4, 141.87, 147.13, 43.1]   ...period.
4  [391.03, 163.9, 60.82, 38.65]            .

                                          points     area
0  [525.83, 3.4, 723.47, 7.29, 722.76, 36.99, 525...  6707.90
1  [535.73, 64.68, 623.41, 67.51, 625.89, 102.87,...  3483.69
2  [626.95, 63.62, 721.7, 63.62, 723.47, 95.44, 6...  3071.27
3  [580.02, 143.61, 724.53, 141.87, 723.66, 184.9...  6341.30
4  [395.2, 163.9, 451.85, 191.94, 445.59, 202.55,...  2350.69
--- Sample from /content/unzipped_dataset/img.csv ---
   Unnamed: 0                id  width  height    set  \
0           0  a4ea732cd3d5948a    840    1024  train
1           1  4bf43a7b2a898044   1024     683  train
2           2  1b55b309b0f50d02   1024     683  train
3           3  00c359f294f7dcd9   1024     680  train
4           4  04b5a37f762b0f51    768    1024  train

                   file_name
0  train/a4ea732cd3d5948a.jpg
1  train/4bf43a7b2a898044.jpg
2  train/1b55b309b0f50d02.jpg
3  train/00c359f294f7dcd9.jpg
4  train/04b5a37f762b0f51.jpg
--- Sample from /content/unzipped_dataset/annot.parquet ---
```

```
                    id          image_id                          bbox  \
0  a4ea732cd3d5948a_1  a4ea732cd3d5948a   [525.83, 3.4, 197.64, 33.94]
1  a4ea732cd3d5948a_2  a4ea732cd3d5948a  [534.67, 64.68, 91.22, 38.19]
2  a4ea732cd3d5948a_3  a4ea732cd3d5948a  [626.95, 63.62, 96.52, 31.82]
3  a4ea732cd3d5948a_4  a4ea732cd3d5948a  [577.4, 141.87, 147.13, 43.1]
4  a4ea732cd3d5948a_5  a4ea732cd3d5948a  [391.03, 163.9, 60.82, 38.65]

   utf8_string                                              points     area
0  Performance  [525.83, 3.4, 723.47, 7.29, 722.76, 36.99, 525...  6707.90
1        Sport  [535.73, 64.68, 623.41, 67.51, 625.89, 102.87,...  3483.69
2        Watch  [626.95, 63.62, 721.7, 63.62, 723.47, 95.44, 6...  3071.27
3   ...period.  [580.02, 143.61, 724.53, 141.87, 723.66, 184.9...  6341.30
4            .  [395.2, 163.9, 451.85, 191.94, 445.59, 202.55,...  2350.69
--- Sample from /content/unzipped_dataset/img.parquet ---
                 id  width  height    set                   file_name
0  a4ea732cd3d5948a    840    1024  train  train/a4ea732cd3d5948a.jpg
1  4bf43a7b2a898044   1024     683  train  train/4bf43a7b2a898044.jpg
2  1b55b309b0f50d02   1024     683  train  train/1b55b309b0f50d02.jpg
3  00c359f294f7dcd9   1024     680  train  train/00c359f294f7dcd9.jpg
4  04b5a37f762b0f51    768    1024  train  train/04b5a37f762b0f51.jpg
--- Sample from /content/unzipped_dataset/TextOCR_0.1_train.json ---
Empty DataFrame
Columns: [Value]
Index: []
--- Sample from /content/unzipped_dataset/train_val_images/train_images ---
                Images
0  0de6722aa3a43476.jpg
1  54e02735ca3dd823.jpg
2  961aa07dd7b5f2d8.jpg
3  b5c2c50202792f10.jpg
4  fdf77957cc71b10d.jpg
```

Achieving Ground Truth

In [13]:

```python
# --- Loading Annotations ---
json_path = "/content/unzipped_dataset/TextOCR_0.1_train.json"  # Path to JSON a
annot_csv_path = "/content/unzipped_dataset/annot.csv"          # CSV annotation
img_csv_path = "/content/unzipped_dataset/img.csv"              # Image metadata
image_folder = "/content/unzipped_dataset/train_val_images/train_images"  # Fold

# Load JSON annotations
with open(json_path, "r") as f:
    json_data = json.load(f)  # Load the JSON annotations

# Load CSV annotations and image metadata
annot_df = pd.read_csv(annot_csv_path)  # Load annotations from CSV
img_metadata_df = pd.read_csv(img_csv_path)  # Load image metadata

# Merge CSV annotations and image metadata
merged_df = pd.merge(
    annot_df, img_metadata_df,
    left_on="image_id", right_on="id",
    how="inner"
)

# Add file paths to the merged DataFrame
merged_df["file_path"] = merged_df["file_name"].apply(
    lambda x: os.path.join(image_folder, x)
)
```

```python
# --- Preparing Ground Truth Data ---
image_text_pairs = []

# Validate JSON structure and debug keys
if "imgs" in json_data and "anns" in json_data and "imgToAnns" in json_data:
    print("JSON keys are valid. Proceeding...")
else:
    print("JSON keys missing. Check JSON structure:")
    print(json_data.keys())

for img_id, metadata in json_data.get("imgs", {}).items():
    file_name = metadata.get("file_name", "")
    corrected_file_name = file_name.replace("train/", "")
    img_path = os.path.join(image_folder, corrected_file_name)

    if not os.path.exists(img_path):
        print(f"Image path not found: {img_path}")
        continue

    # Debugging the annotations linked to the image
    ann_ids = json_data.get("imgToAnns", {}).get(img_id, [])
    if not ann_ids:
        print(f"No annotations found for image ID: {img_id}")
        continue

    text_annotations = []
    for ann_id in ann_ids:
        annotation = json_data["anns"].get(ann_id, {})
        utf8_string = annotation.get("utf8_string", "")
        if not utf8_string:
            print(f"Annotation missing text for ID: {ann_id}")
        else:
            text_annotations.append(utf8_string)

    # Concatenate annotations
    full_text = " ".join(text_annotations)
    image_text_pairs.append({"image_path": img_path, "text": full_text})

if not image_text_pairs:
    print("No valid image-text pairs were found. Debug the JSON annotations furt

# Convert to DataFrame
ground_truth_df = pd.DataFrame(image_text_pairs)

# Display a sample of the prepared ground truth data
print(ground_truth_df.head())
```

```
JSON keys are valid. Proceeding...
                                          image_path  \
0  /content/unzipped_dataset/train_val_images/tra...
1  /content/unzipped_dataset/train_val_images/tra...
2  /content/unzipped_dataset/train_val_images/tra...
3  /content/unzipped_dataset/train_val_images/tra...
4  /content/unzipped_dataset/train_val_images/tra...

                                                text
0  Performance Sport Watch ...period. . 400 300 1...
1  400 Z 7 at nLa A. James LYNCH REAL ESTATE 781....
```

```
2  CAOL ILA DISTILLERY 1996 GLE MALT SCOTCH WHISK...
3                                        G-ATCO HUSKY +
4  OUR NEIGHBORS, THE FRIENDS . . . 1 Muhomah . f...
```

Ground Truth Image Sample

In [14]:

```python
def visualize_ground_truth(image_path, image_annotations):
    """
    Visualize the ground truth annotations (bounding boxes and text) on the image
    """
    image = Image.open(image_path)
    fig, ax = plt.subplots(figsize=(10, 10))
    ax.imshow(image)

    for annotation in image_annotations:
        bbox = annotation["bbox"]  # [x, y, width, height]
        text = annotation["utf8_string"]

        # Draw bounding box
        rect = patches.Rectangle(
            (bbox[0], bbox[1]), bbox[2], bbox[3], linewidth=2, edgecolor="red",
        )
        ax.add_patch(rect)

        # Display text
        ax.text(
            bbox[0], bbox[1] - 10, text, fontsize=12, color="blue",
            bbox=dict(facecolor="white", alpha=0.7, edgecolor="none", boxstyle="
        )

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

In [17]:

```python
# Function to visualize the image before annotations
def visualize_before_merge(image_path):
    """
    Display the image without annotations (before merging).

    Args:
    - image_path (str): Path to the image file.
    """
    if not os.path.exists(image_path):
        print(f"Image not found: {image_path}")
        return

    # Load the image
    image = plt.imread(image_path)

    # Display the image
    plt.figure(figsize=(10, 8))
    plt.imshow(image)
    plt.title("Before Ground Truth Merging", fontsize=16)
    plt.axis('off')
    plt.show()

# Function to visualize the image after annotations
def visualize_after_merge(image_path, annotations):
```

```
def visualize_after_merge(image_path, annotations):
    """
    Visualize the image with bounding boxes and labels (after merging).

    Args:
    - image_path (str): Path to the image file.
    - annotations (list of tuples): List of (label, bbox) tuples.
    """
    if not os.path.exists(image_path):
        print(f"Image not found: {image_path}")
        return

    # Load the image
    image = plt.imread(image_path)

    # Set up the plot
    fig, ax = plt.subplots(1, figsize=(15, 10))
    ax.imshow(image)

    # Add bounding boxes and labels
    for label, bbox in annotations:
        # Ensure bbox is a list (if stored as a string)
        if isinstance(bbox, str):
            bbox = eval(bbox)

        # Draw the bounding box
        rect = patches.Rectangle(
            (bbox[0], bbox[1]), bbox[2], bbox[3], linewidth=2, edgecolor="red",
        )
        ax.add_patch(rect)

        # Add the label above the bounding box
        ax.text(
            bbox[0], bbox[1] - 10, label, fontsize=10, color="blue",
            bbox=dict(facecolor="white", alpha=0.8)
        )

    plt.axis('off')
    plt.title("After Ground Truth Merging", fontsize=16)
    plt.show()


# File path for the specific image
image_path = "/content/unzipped_dataset/train_val_images/train_images/4bf43a7b2a

# Define the annotations (label and bbox pairs)
annotations = [
    ("400", [429.44, 163.75, 27.52, 13.0]),
    ("Z", [2.52, 206.33, 14.29, 18.56]),
    ("7", [1.21, 229.65, 5.91, 11.33]),
    ("at", [8.11, 232.44, 8.54, 8.7]),
    ("nLa", [0.23, 246.23, 17.24, 12.81]),
    ("A.", [138.01, 192.86, 13.63, 11.33]),
    ("James", [153.61, 193.36, 38.43, 10.83]),
    ("LYNCH", [115.51, 202.88, 98.7, 27.43]),
    ("REAL", [94.32, 231.13, 24.47, 10.18]),
    ("ESTATE", [119.61, 231.29, 34.98, 10.18]),
    ("781.599.1599", [96.13, 240.32, 57.48, 11.17]),
    ("INSURANCE", [181.53, 230.96, 54.68, 9.69]),
    ("781.598.4700", [180.38, 240.65, 57.31, 10.02]),
    (".", [123.88, 252.48, 82.44, 9.52]),
```

```
    (".", [306.66, 215.53, 13.14, 9.85]),
    (".", [321.12, 217.66, 13.46, 10.18]),
    (".", [508.81, 382.92, 19.62, 6.98]),
    ("12", [439.01, 412.72, 71.5, 46.03]),
    (".", [571.09, 216.87, 9.19, 9.86]),
    (".", [656.64, 282.71, 32.03, 32.88]),
    ("23", [676.66, 292.43, 40.31, 41.17]),
    ("n's", [672.66, 197.52, 23.62, 19.94]),
    ("Roast", [696.93, 197.95, 47.67, 19.51]),
    ("Beef", [745.04, 195.79, 42.47, 26.65]),
    ("Seafood", [692.6, 218.97, 66.31, 25.79]),
    ("stbeef.com", [725.32, 245.84, 55.91, 18.85]),
    ("Life", [839.95, 205.97, 28.6, 16.47]),
    ("Care", [837.35, 219.41, 37.92, 14.73]),
    ("Center", [842.77, 229.59, 52.87, 15.82]),
    ("of", [836.05, 243.46, 9.32, 8.23]),
    ("the", [843.85, 243.68, 11.92, 8.01]),
    ("North", [854.47, 242.16, 27.08, 10.4]),
    ("Shore", [880.04, 242.38, 27.52, 10.61]),
    ("111", [811.92, 255.67, 13.63, 9.69]),
    ("Binch", [826.37, 255.02, 19.87, 11.33]),
    ("Street/", [846.89, 255.67, 25.46, 10.68]),
    ("Lyna,", [872.18, 256.16, 21.35, 12.16]),
    ("MA", [893.53, 256.66, 15.44, 10.01]),
    ("01902", [907.82, 256.49, 24.63, 10.18]),
    ("Her", [1003.13, 216.15, 19.87, 10.51]),
    ("Ea", [1004.11, 231.75, 18.72, 14.12]),
    (".", [637.9, 333.09, 21.34, 12.48]),
    ("KNEE", [597.52, 572.86, 23.19, 24.49]),
    ("SAVER", [602.72, 579.37, 26.01, 26.0]),
    ("KNEE", [375.82, 563.72, 23.62, 22.97]),
    ("SAVER", [371.92, 570.22, 29.25, 26.44]),
    (".", [523.51, 264.31, 17.74, 15.11]),
]

# Visualize the image before merging
print("Visualizing before merging:")
visualize_before_merge(image_path)

# Visualize the image after merging
print("\nVisualizing after merging:")
visualize_after_merge(image_path, annotations)
```

```
Visualizing before merging:
```

Visualizing after merging:

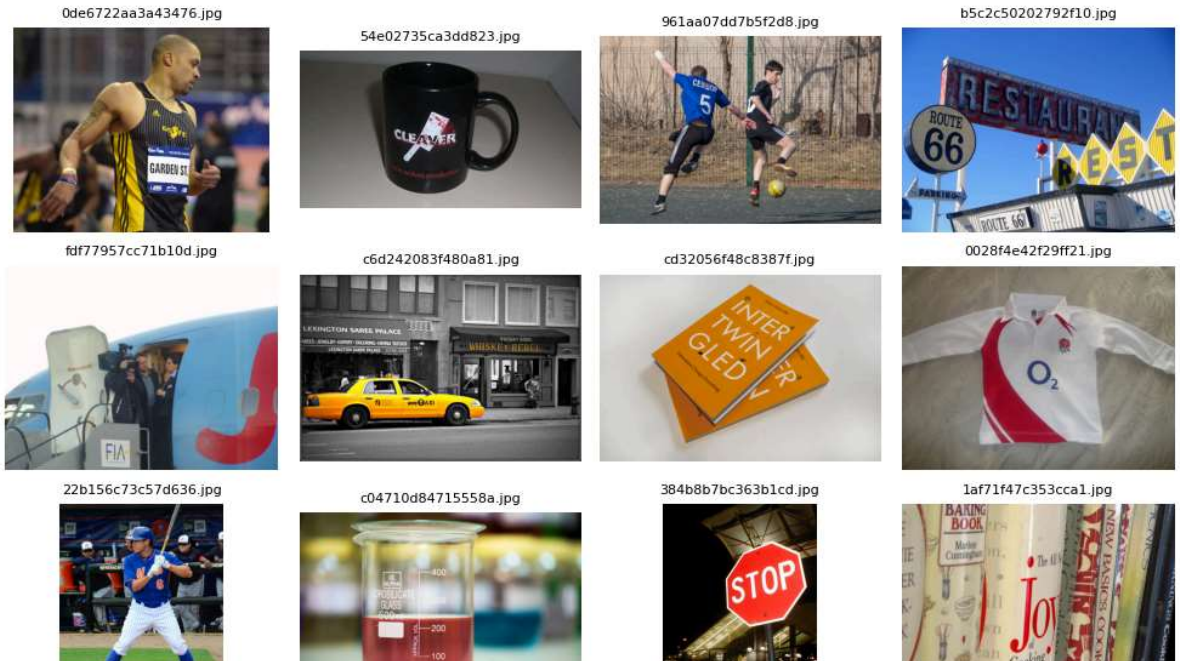
Ground Truth *was achieved by merging annotations, metadata, and image files into a unified dataset, ensuring each image was accurately linked with its bounding boxes, text annotations, and metadata such as dimensions and file paths. Using the JSON annotation file (TextOCR_0.1_train.json), annotation CSV (annot.csv), and image metadata (img.csv), I performed careful validation to confirm alignment between image_path, utf8_string (text annotations), and bbox (bounding box coordinates). For example, in the image "4bf43a7b2a898044.jpg," annotations include bounding boxes for text such as "400," "Seafood," and "KNEE SAVER," each accurately positioned to match its visual location. This visual linkage ensures a direct association between the image and its textual content, aiding in effective training and evaluation of the OCR model. Ground truth is crucial as it provides the reference data for metrics like Character Error Rate (CER) and Word Error Rate (WER) and enables the visualization of annotated images to address issues like missing or misaligned annotations. High-quality ground truth also enhances the model's learning process by establishing reliable text-image mappings and supports the refinement of preprocessing to maintain alignment between input data and expected outputs.*

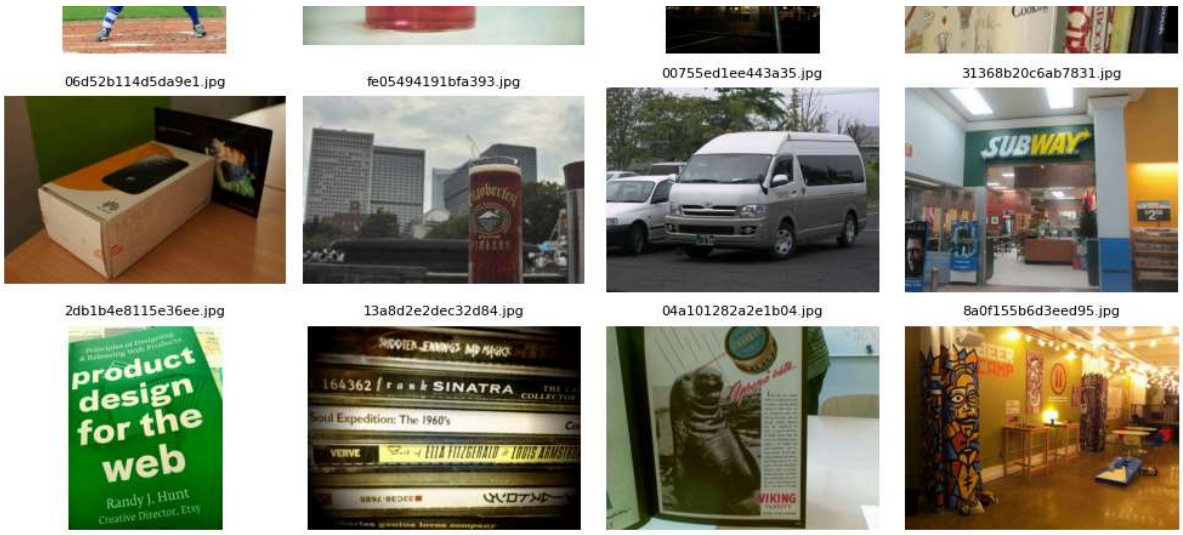
Display Data Images

In [15]:

```
# Update the folder path to the correct image directory
unzipped_folder = "/content/unzipped_dataset/train_val_images/train_images"


def display_sample_images(folder, num_images=20):
    valid_extensions = ('.png', '.jpg', '.jpeg', '.bmp', '.tiff')
    image_files = [f for f in os.listdir(folder) if f.lower().endswith(valid_ext
    image_files = image_files[:num_images]  # Limit to the first `num_images`

    if not image_files:
        print("No images found in the folder.")
        return

    # Display images in a grid
    plt.figure(figsize=(10, 10))
    for i, image_name in enumerate(image_files, start=1):
        image_path = os.path.join(folder, image_name)
        image = cv2.imread(image_path)
        if image is not None:
            image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)  # Convert BGR to RGB
            plt.subplot(5, 4, i)  # Create a grid of 5 rows and 4 columns
            plt.imshow(image)
            plt.title(image_name, fontsize=8)
            plt.axis('off')
        else:
            print(f"Unable to read image: {image_name}")
    plt.tight_layout()
    plt.show()


# Display the first 20 images
print("Displaying the first 20 images from the dataset...")
display_sample_images(unzipped_folder)
```

```
Displaying the first 20 images from the dataset...
```





Data Cleaning

In [16]:

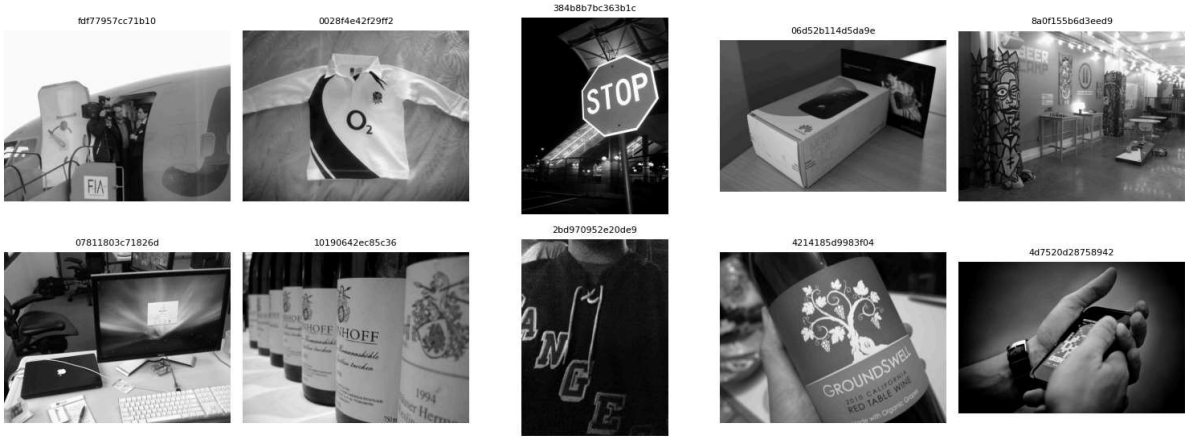
```
# Thresholds for quality checks
BRIGHTNESS_THRESHOLD = 50
CONTRAST_THRESHOLD = 20
SHARPNESS_THRESHOLD = 100

# Paths for input and output folders
input_folder = "/content/unzipped_dataset/train_val_images/train_images"
ocr_ready_folder = "/content/test_images"  # Folder for OCR-ready images
non_ocr_ready_folder = "/content/disposed_images"  # Folder for non-OCR-ready im
os.makedirs(ocr_ready_folder, exist_ok=True)  # Ensure OCR-ready folder exists
os.makedirs(non_ocr_ready_folder, exist_ok=True)  # Ensure non-OCR-ready folder

# Functions for image quality evaluation
def calculate_brightness(image):
    """Calculate brightness of an image."""
    pil_image = Image.fromarray(image)
    stat = ImageStat.Stat(pil_image)
    return stat.mean[0]

def calculate_contrast(image):
    """Calculate contrast of an image."""
    gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
    return gray.std()

def calculate_sharpness(image):
    """Calculate sharpness of an image."""
    gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
    return cv2.Laplacian(gray, cv2.CV_64F).var()

def contains_text(image_path):
    """Check if an image contains text using Tesseract OCR."""
    image = cv2.imread(image_path, cv2.IMREAD_GRAYSCALE)
    text = pytesseract.image_to_string(image)
    return len(text.strip()) > 0

# Function to clean and categorize images
def clean_images(input_folder, ocr_ready_folder, non_ocr_ready_folder):
    valid_images = []
    non_ocr_ready_images = []
```

```
    for image_name in tqdm(os.listdir(input_folder), desc="Processing Images", u
        image_path = os.path.join(input_folder, image_name)
        if not image_name.lower().endswith(('.png', '.jpg', '.jpeg', '.bmp', '.t
            continue

        # Read and evaluate the image
        image = cv2.imread(image_path)
        if image is None:
            continue  # Skip unreadable images

        try:
            # Calculate quality metrics
            brightness = calculate_brightness(image)
            contrast = calculate_contrast(image)
            sharpness = calculate_sharpness(image)

            # Check if the image meets OCR readiness criteria or contains text
            if (
                brightness >= BRIGHTNESS_THRESHOLD and
                contrast >= CONTRAST_THRESHOLD and
                sharpness >= SHARPNESS_THRESHOLD
            ) or contains_text(image_path):
                # Save OCR-ready image
                copyfile(image_path, os.path.join(ocr_ready_folder, image_name))
                valid_images.append(image_name)
            else:
                # Save non-OCR-ready image
                copyfile(image_path, os.path.join(non_ocr_ready_folder, image_na
                non_ocr_ready_images.append(image_name)
        except Exception as e:
            print(f"Error processing {image_name}: {e}")

    return valid_images, non_ocr_ready_images

# Function to visualize images in a 2x5 grid
def visualize_images(folder, title, num_images=10):
    """Display images in a 2x5 grid."""
    files = os.listdir(folder)[:num_images]  # Get the first `num_images` files
    rows, cols = 2, 5  # Define grid dimensions
    plt.figure(figsize=(15, 6))
    for i, file in enumerate(files, 1):
        img_path = os.path.join(folder, file)
        img = cv2.imread(img_path, cv2.IMREAD_GRAYSCALE)  # Load image in graysc
        if img is not None:
            plt.subplot(rows, cols, i)
            plt.imshow(img, cmap='gray')
            plt.title(file[:15], fontsize=8)  # Truncate file names for readabil
            plt.axis('off')
    plt.suptitle(title, fontsize=16)
    plt.tight_layout()
    plt.show()

# Run the cleaning process
ocr_ready_images, non_ocr_ready_images = clean_images(input_folder, ocr_ready_fo

# Summary of results
print(f"\nTotal images processed: {len(os.listdir(input_folder))}")
print(f"Total OCR-ready images saved in '{ocr_ready_folder}': {len(ocr_ready_ima
print(f"Total non-OCR-ready images saved in '{non_ocr_ready_folder}': {len(non_o
```

```
# Visualize OCR-ready images
print(f"Visualizing first 10 OCR-ready images from {ocr_ready_folder}...")
visualize_images(ocr_ready_folder, title="OCR-Ready Images (Cleaned)")

# Visualize Non-OCR-ready images
print(f"Visualizing first 10 non-OCR-ready images from {non_ocr_ready_folder}...
visualize_images(non_ocr_ready_folder, title="Non-OCR-Ready Images (Disposed)")
```

```
Processing Images: 100%|██████████| 25119/25119 [34:34<00:00, 12.11image/s]
Total images processed: 25119
Total OCR-ready images saved in '/content/test_images': 21266
Total non-OCR-ready images saved in '/content/disposed_images': 3853
Visualizing first 10 OCR-ready images from /content/test_images...
```


```
Visualizing first 10 non-OCR-ready images from /content/disposed_images...
```



Exploratory Data Analysis

In [58]:

```
# Paths
clean_folder = "/content/test_images"  # Folder with clean images
output_csv = "/content/eda_results.csv"  # CSV to save EDA results

# Helper functions for feature extraction
def calculate_brightness(image):
    """Calculate brightness of an image."""
    image = Image.fromarray(image)
    stat = ImageStat.Stat(image)
    return stat.mean[0]
```

```
def calculate_contrast(image):
    """Calculate contrast of an image."""
    gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
    return gray.std()

def calculate_sharpness(image):
    """Calculate sharpness of an image."""
    gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
    laplacian = cv2.Laplacian(gray, cv2.CV_64F).var()
    return laplacian

# Process preprocessed images and extract features
def process_images_for_eda(folder):
    """Extract brightness, contrast, and sharpness for all valid images."""
    data = []
    valid_extensions = ('.png', '.jpg', '.jpeg', '.bmp', '.tiff')
    image_files = sorted([f for f in os.listdir(folder) if f.lower().endswith(va

    # Add progress bar for processing
    for image_name in tqdm(image_files, desc="Analyzing Images", unit="image"):
        image_path = os.path.join(folder, image_name)

        # Read image
        image = cv2.imread(image_path)
        if image is None:
            print(f"Unreadable image file: {image_name}")
            continue

        # Extract features
        try:
            brightness = calculate_brightness(image)
            contrast = calculate_contrast(image)
            sharpness = calculate_sharpness(image)
            height, width = image.shape[:2]
            data.append({
                "Image": image_name,
                "Brightness": brightness,
                "Contrast": contrast,
                "Sharpness": sharpness,
                "Width": width,
                "Height": height,
                "Aspect Ratio": width / height if height > 0 else None
            })
        except Exception as e:
            print(f"Error processing image {image_name}: {e}")

    return pd.DataFrame(data)
```

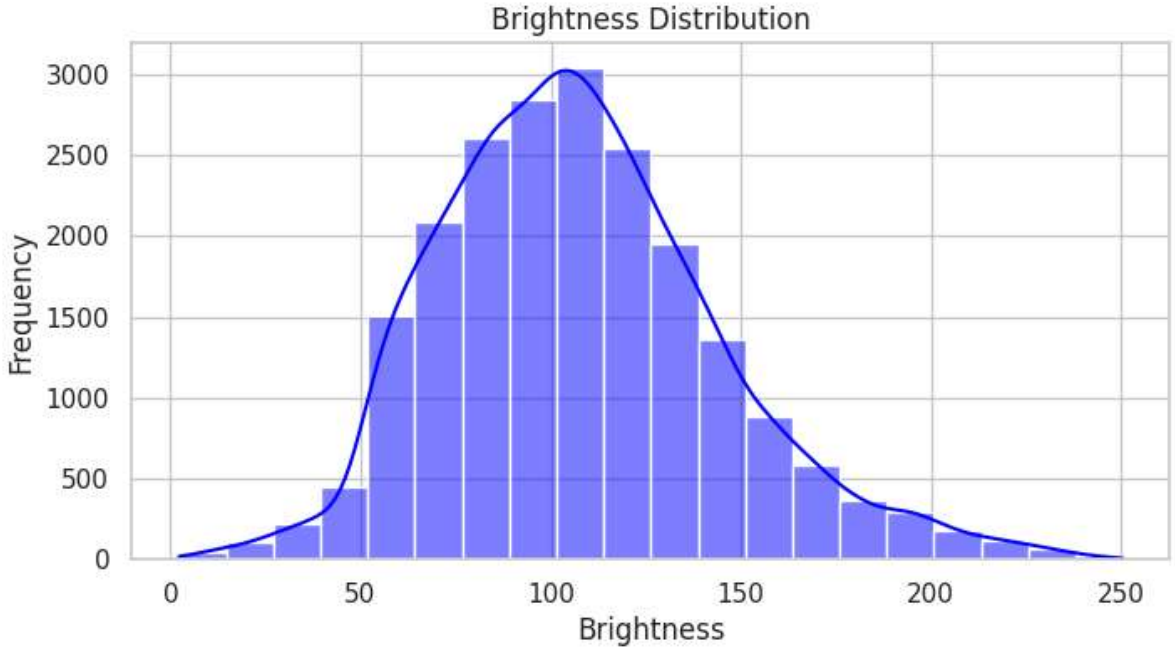
In [59]:

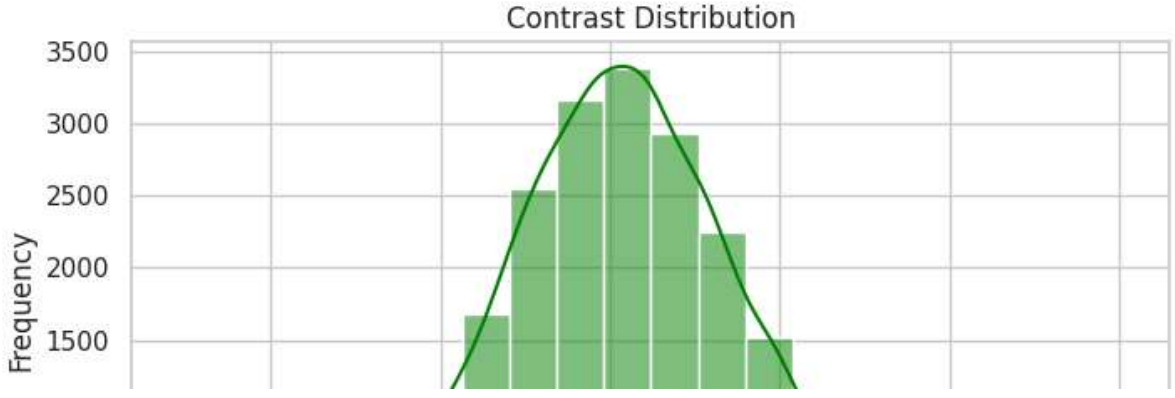
```
# Extract features from clean images
print("Starting EDA...")
df = process_images_for_eda(clean_folder)

# Save EDA results and perform visualizations
if not df.empty:
    # Save results to CSV
    df.to_csv(output_csv, index=False)
    print(f"EDA results saved to {output_csv}")
```

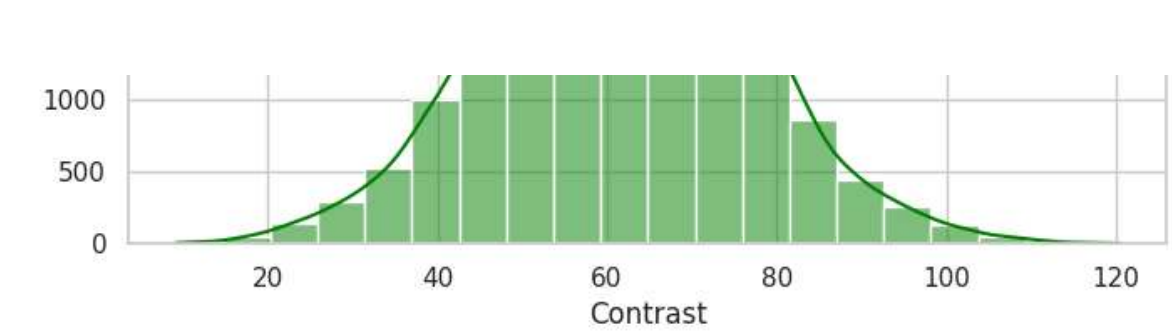
```
    # Summary statistics
    print("Summary Statistics:")
    print(df.describe())

    # Visualizations
    sns.set(style="whitegrid")

    # Brightness Distribution
    plt.figure(figsize=(8, 4))
    sns.histplot(df["Brightness"], bins=20, kde=True, color="blue")
    plt.title("Brightness Distribution")
    plt.xlabel("Brightness")
    plt.ylabel("Frequency")
    plt.show()

    # Contrast Distribution
    plt.figure(figsize=(8, 4))
    sns.histplot(df["Contrast"], bins=20, kde=True, color="green")
    plt.title("Contrast Distribution")
    plt.xlabel("Contrast")
    plt.ylabel("Frequency")
    plt.show()

    # Sharpness Distribution
    plt.figure(figsize=(8, 4))
    sns.histplot(df["Sharpness"], bins=20, kde=True, color="red")
    plt.title("Sharpness Distribution")
    plt.xlabel("Sharpness")
    plt.ylabel("Frequency")
    plt.show()

    # Image Dimensions Distribution
    plt.figure(figsize=(8, 4))
    sns.histplot(df["Width"], bins=20, kde=True, color="orange", label="Width")
    sns.histplot(df["Height"], bins=20, kde=True, color="purple", label="Height"
    plt.title("Image Dimensions Distribution")
    plt.xlabel("Dimension")
    plt.ylabel("Frequency")
    plt.legend()
    plt.show()

    # Aspect Ratio Distribution
    plt.figure(figsize=(8, 4))
    sns.histplot(df["Aspect Ratio"], bins=20, kde=True, color="cyan")
    plt.title("Aspect Ratio Distribution")
    plt.xlabel("Aspect Ratio (Width / Height)")
    plt.ylabel("Frequency")
    plt.show()

    # Pairplot for relationships
    sns.pairplot(df, vars=["Brightness", "Contrast", "Sharpness"], diag_kind="kd
    plt.show()

    # Correlation Heatmap
    plt.figure(figsize=(8, 4))
    corr = df[["Brightness", "Contrast", "Sharpness", "Width", "Height", "Aspect
    sns.heatmap(corr, annot=True, cmap="coolwarm", fmt=".2f")
    plt.title("Feature Correlation Heatmap")
    plt.show()
```

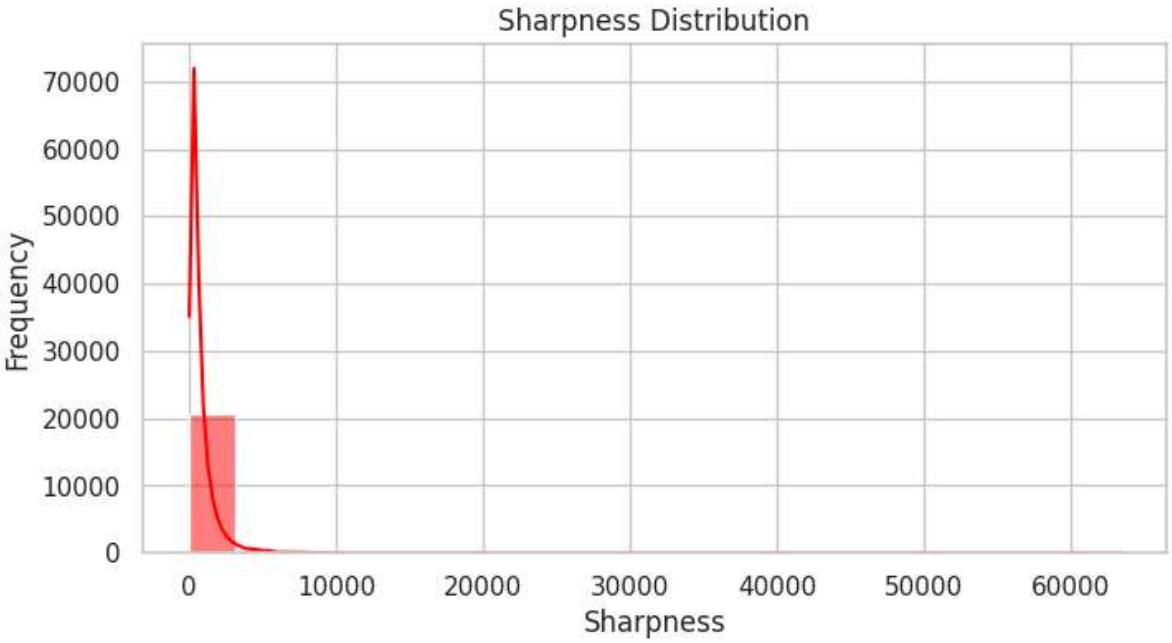
```
else:
    print("No valid images processed. Ensure the clean folder contains valid imag
```

```
Starting EDA...
Analyzing Images: 100%|████████| 21266/21266 [06:14<00:00, 56.75image/s]
EDA results saved to /content/eda_results.csv
Summary Statistics:
         Brightness      Contrast     Sharpness         Width        Height  \
count  21266.000000  21266.000000  21266.000000  21266.000000  21266.000000
mean     107.533578     61.363905    774.817362    947.181463    813.612339
std       37.141491     14.715217   1187.632535    149.536513    160.033975
min        2.290301      9.156127      3.986215    256.000000    257.000000
25%       81.443593     51.821058    225.975420    926.250000    683.000000
50%      104.517960     61.242335    447.927146   1024.000000    768.000000
75%      129.374201     70.807710    902.185206   1024.000000   1024.000000
max      250.397028    120.472789  63304.231738   4608.000000   3456.000000

       Aspect Ratio
count  21266.000000
mean       1.230953
std        0.363947
min        0.250000
25%        0.994141
50%        1.333333
75%        1.499268
max        3.984436
```






1000
500
0
20
40
60
80
100
120
Contrast


Sharpness Distribution
70000
60000
50000
40000
30000
20000
10000
0
Frequency
0
10000
20000
30000
40000
50000
60000
Sharpness

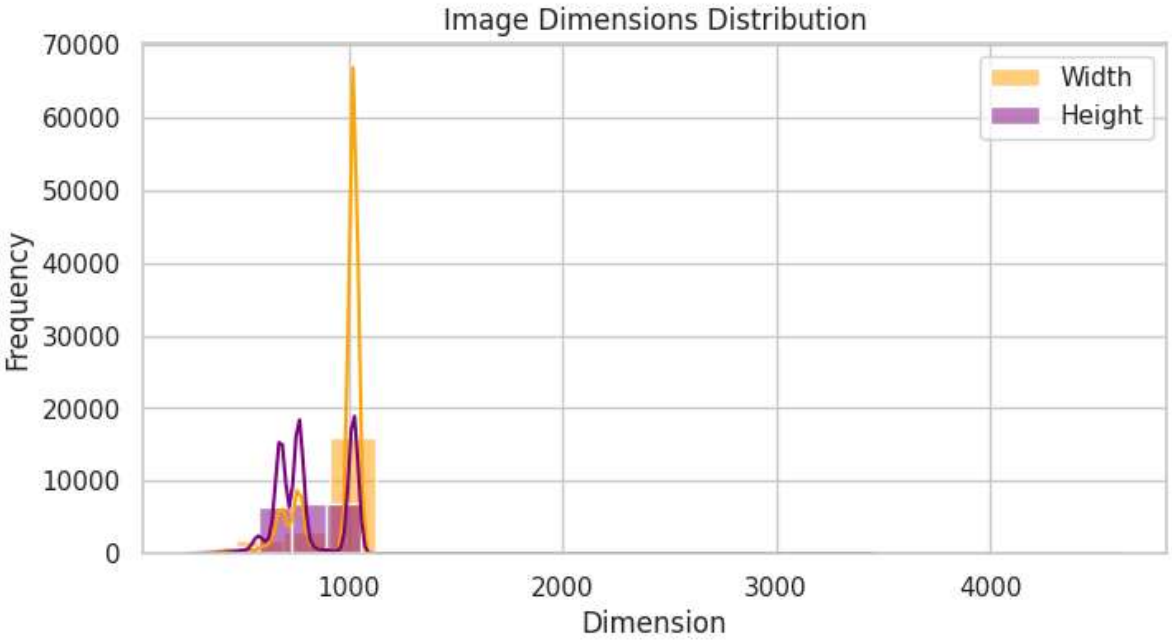
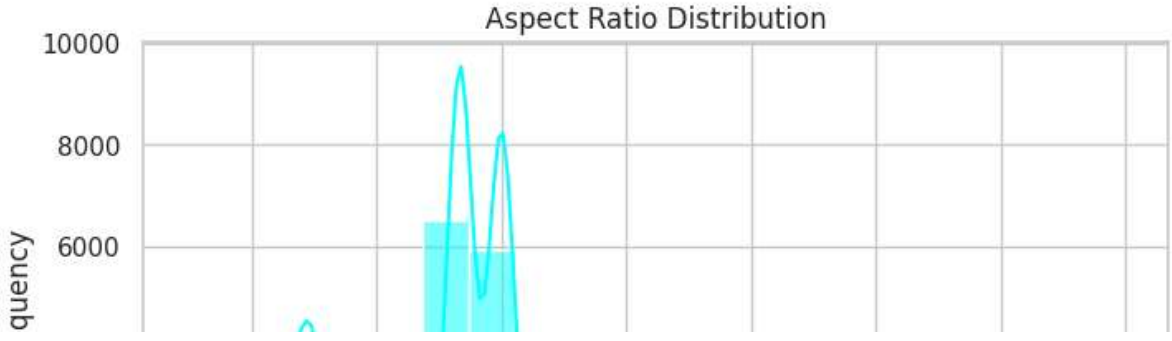
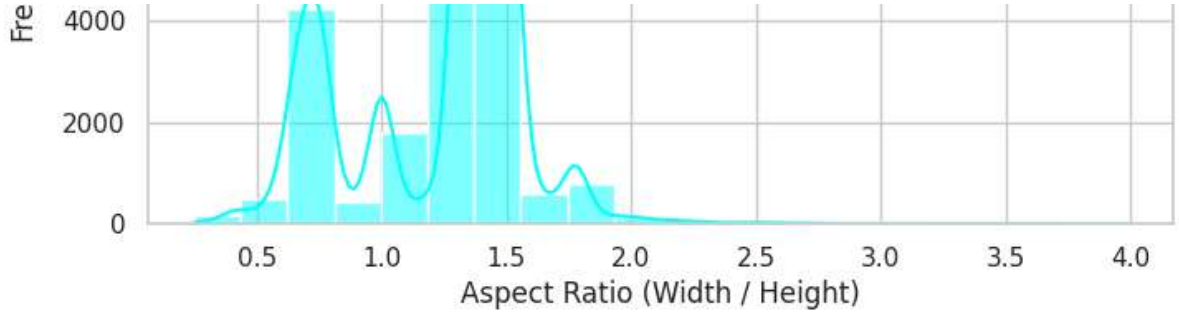
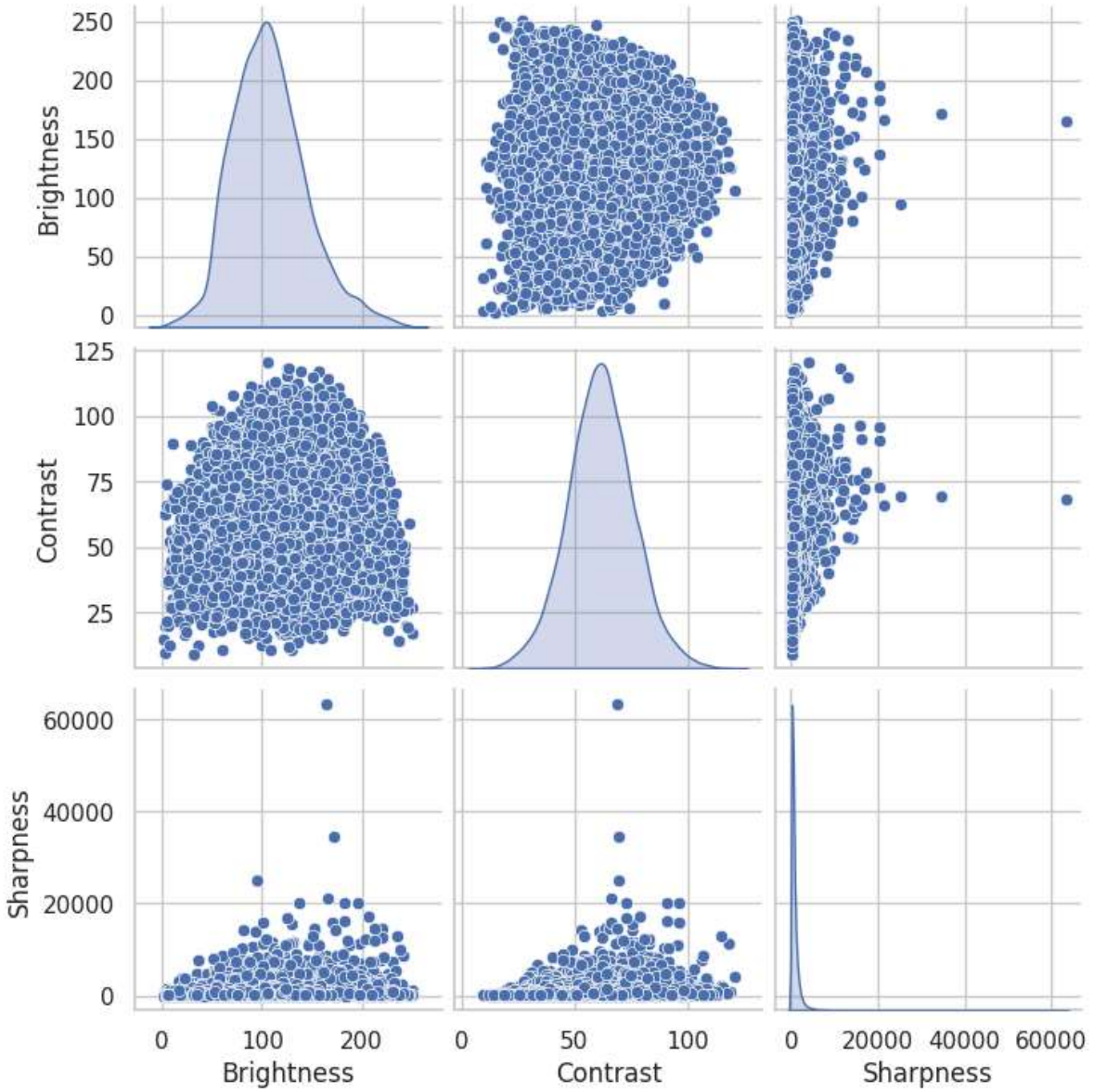
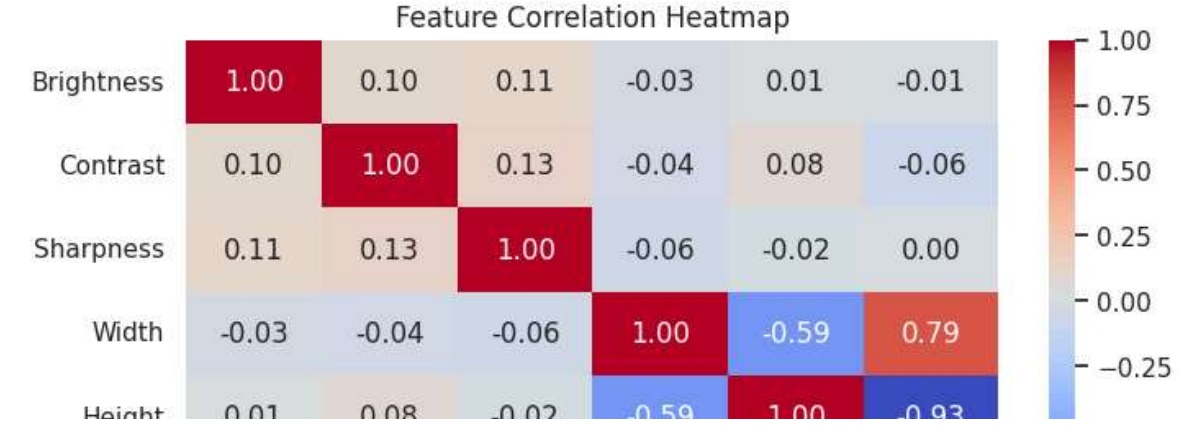


Image Dimensions Distribution
Width
Height
70000
60000
50000
40000
30000
20000
10000
0
Frequency
1000
2000
3000
4000
Dimension


Aspect Ratio Distribution
10000
8000
6000
quency


Fre
4000
2000
0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
Aspect Ratio (Width / Height)


Brightness
250
200
150
100
50
0
Contrast
125
100
75
50
25
Sharpness
60000
40000
20000
0
0
100
200
Brightness
0
50
100
Contrast
0
20000
40000
60000
Sharpness


Feature Correlation Heatmap
Brightness
Contrast
Sharpness
Width
Height
1.00
0.10
0.11
-0.03
0.01
-0.01
0.10
1.00
0.13
-0.04
0.08
-0.06
0.11
0.13
1.00
-0.06
-0.02
0.00
-0.03
-0.04
-0.06
1.00
-0.59
0.79
0.01
0.08
-0.02
-0.59
1.00
-0.93
1.00
0.75
0.50
0.25
0.00
−0.25

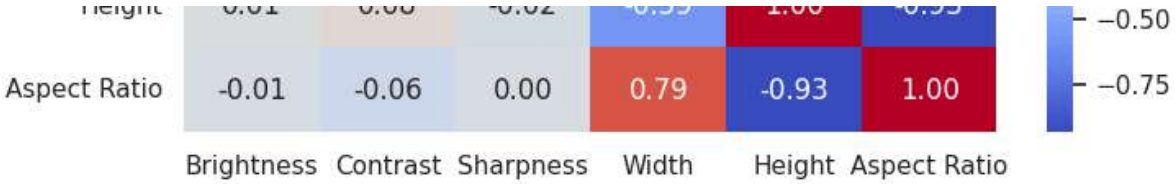


Image Preprocessing

In [41]:

```python
# Input folder for preprocessing (use OCR-ready folder from cleaning step)
input_folder = ocr_ready_folder  # OCR-ready folder from cleaning
output_folder = "/content/output_images"  # Folder for preprocessed images
os.makedirs(output_folder, exist_ok=True)  # Ensure preprocessed folder exists


def preprocess_image(image_path, output_path):
    """
    Preprocess the image by applying grayscale conversion, Gaussian blur,
    binarization, deskewing, and controlled sharpening.
    """
    try:
        # Load the image
        image = cv2.imread(image_path, cv2.IMREAD_GRAYSCALE)

        # Validate image loading
        if image is None:
            print(f"Could not read image: {image_path}")
            return

        # Apply Gaussian blur to reduce noise
        blurred = cv2.GaussianBlur(image, (5, 5), 0)

        # Apply adaptive thresholding for binarization
        binary = cv2.adaptiveThreshold(
            blurred, 255,
            cv2.ADAPTIVE_THRESH_GAUSSIAN_C,
            cv2.THRESH_BINARY, 11, 2
        )

        # Deskew the image
        coords = np.column_stack(np.where(binary > 0))
        angle = cv2.minAreaRect(coords)[-1]
        if angle < -45:
            angle = -(90 + angle)
        else:
            angle = -angle

        # Limit deskew rotation angles to avoid overcorrection
        if abs(angle) > 20:
            print(f"Skipping excessive rotation for: {image_path}")
            return

        # Rotate image to deskew
        h, w = binary.shape[:2]
        center = (w // 2, h // 2)
        M = cv2.getRotationMatrix2D(center, angle, 1.0)
        deskewed = cv2.warpAffine(
            binary, M, (w, h),
            flags=cv2.INTER_CUBIC,
```

```
            borderMode=cv2.BORDER_REPLICATE
        )

        # Apply controlled sharpening
        kernel = np.array([[0, -1, 0], [-1, 5, -1], [0, -1, 0]])
        sharpened = cv2.filter2D(deskewed, -1, kernel)

        # Save preprocessed image
        cv2.imwrite(output_path, sharpened)

    except Exception as e:
        print(f"Error processing {image_path}: {e}")


def preprocess_images(input_folder, output_folder):
    """
    Preprocess all images in the input folder and save to the output folder.
    """
    for image_name in tqdm(
        os.listdir(input_folder),
        desc="Preprocessing Images",
        unit="image"
    ):
        if image_name.lower().endswith(('.png', '.jpg', '.jpeg', '.bmp', '.tiff'
            image_path = os.path.join(input_folder, image_name)
            output_path = os.path.join(output_folder, image_name)
            preprocess_image(image_path, output_path)


def visualize_images(folder, title="Images"):
    """
    Visualize the first 5 images in the given folder.
    """
    images = os.listdir(folder)[:5]  # Limit to the first 5 images
    plt.figure(figsize=(15, 6))
    for i, image_name in enumerate(images):
        image_path = os.path.join(folder, image_name)
        img = cv2.imread(image_path, cv2.IMREAD_GRAYSCALE)
        if img is not None:
            plt.subplot(2, 5, i + 1)
            plt.imshow(img, cmap='gray')
            plt.title(image_name)
            plt.axis('off')
    plt.suptitle(title)
    plt.show()

# Visualize the first 5 preprocessed images
print(f"Visualizing first 5 preprocessed images from {output_folder}...")
visualize_images(output_folder, title="Preprocessed Images")
```

```
Visualizing first 5 preprocessed images from /content/output_images...
```

Modeling Methods: EasyOCR and TcOCR

In [42]:

```
# EasyOCR, TrOCR, and PaddleOCR Model Setup
# Use the folder from the preprocessed images
output_folder = "/content/output_images"

# Instantiate EasyOCR Reader
def get_easyocr_reader():
    # Languages can be adjusted depending on the dataset
    reader = easyocr.Reader(["en"], gpu=torch.cuda.is_available())
    return reader

reader_easyocr = get_easyocr_reader()

# Preparing Dataset for OCR
def create_dataset(folder, limit=None):
    image_files = [f for f in os.listdir(folder) if f.lower().endswith(('.png',
    if limit:
        image_files = image_files[:limit]

    dataset = []
    for image_file in image_files:
        img_path = os.path.join(folder, image_file)
        dataset.append(img_path)
    return dataset

# Create datasets (e.g., training and validation datasets)
train_dataset = create_dataset(ocr_ready_folder, limit=2000)  # Use a subset for
validation_dataset = create_dataset(ocr_ready_folder, limit=200)  # For validati
```

In [43]:

```
# Modeling Methods: EasyOCR and TrOCR
# We are using two OCR models: EasyOCR and TrOCR. These 2 models are pre-trained

# Load pre-trained TrOCR model and processor
processor_trocr = TrOCRProcessor.from_pretrained("microsoft/trocr-base-printed")
model_trocr = VisionEncoderDecoderModel.from_pretrained("microsoft/trocr-base-pr
```

```
preprocessor_config.json:   0%|          | 0.00/224 [00:00<?, ?B/s]
tokenizer_config.json:   0%|          | 0.00/1.12k [00:00<?, ?B/s]
vocab.json:   0%|          | 0.00/899k [00:00<?, ?B/s]
merges.txt:   0%|          | 0.00/456k [00:00<?, ?B/s]
special_tokens_map.json:   0%|          | 0.00/772 [00:00<?, ?B/s]
config.json:   0%|          | 0.00/4.13k [00:00<?, ?B/s]
model.safetensors:   0%|          | 0.00/1.33G [00:00<?, ?B/s]
generation_config.json:   0%|          | 0.00/190 [00:00<?, ?B/s]
```

Displayed as shown (above)

In [44]:

```python
# Evaluation Metrics for OCR
def evaluate_ocr(model_type, reader, dataset, ground_truths):
    total_wer, total_cer = 0, 0
    count = 0

    for image_path, ground_truth in tqdm(zip(dataset, ground_truths), desc=f"Eva
        if model_type == "EasyOCR":
            result = reader.readtext(image_path, detail=0)  # EasyOCR output
            predicted_text = ' '.join(result)
        elif model_type == "TrOCR":
            # Preprocess image for TrOCR
            image = Image.open(image_path).convert("RGB")
            pixel_values = processor_trocr(images=image, return_tensors="pt").pi
            generated_ids = model_trocr.generate(pixel_values)
            predicted_text = processor_trocr.batch_decode(generated_ids, skip_sp
        else:
            raise ValueError("Invalid OCR model type specified.")

        count += 1
        # Calculate word error rate (WER) and character error rate (CER)
        total_wer += wer(ground_truth, predicted_text)
        total_cer += cer(ground_truth, predicted_text)

    average_wer = total_wer / count if count > 0 else None
    average_cer = total_cer / count if count > 0 else None

    return average_wer, average_cer
```

In [45]:

```python
# To proceed with evaluation, we need ground truth text for each image (This requ
# If you have such dataset, replace the below line with actual ground truth load
# Placeholder for ground truth (can use the `ground_truth_df` for this purpose i
ground_truths = ground_truth_df["text"].tolist()[:len(train_dataset)]  # Adjust

# Validation and Performance Metrics
# Evaluate EasyOCR
print("Starting evaluation of EasyOCR model...")
average_wer_easyocr, average_cer_easyocr = evaluate_ocr("EasyOCR", reader_easyoc
print(f"\nEasyOCR - Average Word Error Rate (WER): {average_wer_easyocr:.2f}")
print(f"EasyOCR - Average Character Error Rate (CER): {average_cer_easyocr:.2f}"
```

```
Starting evaluation of EasyOCR model...
Evaluating Images (EasyOCR): 100%|██████████| 2000/2000 [08:34<00:00,  3.88it/s]
EasyOCR - Average Word Error Rate (WER): 3.10
EasyOCR - Average Character Error Rate (CER): 3.87
```

In [46]:

```python
# Evaluate TrOCR
```

```
print("Starting evaluation of TrOCR model...")
average_wer_trocr, average_cer_trocr = evaluate_ocr("TrOCR", None, train_dataset
print(f"\nTrOCR - Average Word Error Rate (WER): {average_wer_trocr:.2f}")
print(f"TrOCR - Average Character Error Rate (CER): {average_cer_trocr:.2f}")
```

```
Starting evaluation of TrOCR model...
Evaluating Images (TrOCR): 100%|██████████| 2000/2000 [20:36<00:00,  1.62it/s]
TrOCR - Average Word Error Rate (WER): 1.00
TrOCR - Average Character Error Rate (CER): 0.99
```

Note: For TrOCR, the evaluation uses processor_trocr and model_trocr, and the reader parameter is not referenced. This makes passing None acceptable when evaluating TrOCR.

In [50]:

```
# Saving Results to CSV for Further Analysis
results_csv = "/content/ocr_evaluation_results.csv"
with open(results_csv, "w") as file:
    file.write(f"Model,WER,CER\n")
    file.write(f"EasyOCR,{average_wer_easyocr:.2f},{average_cer_easyocr:.2f}\n")
    file.write(f"TrOCR,{average_wer_trocr:.2f},{average_cer_trocr:.2f}\n")

print(f"Evaluation metrics saved to {results_csv}")
```

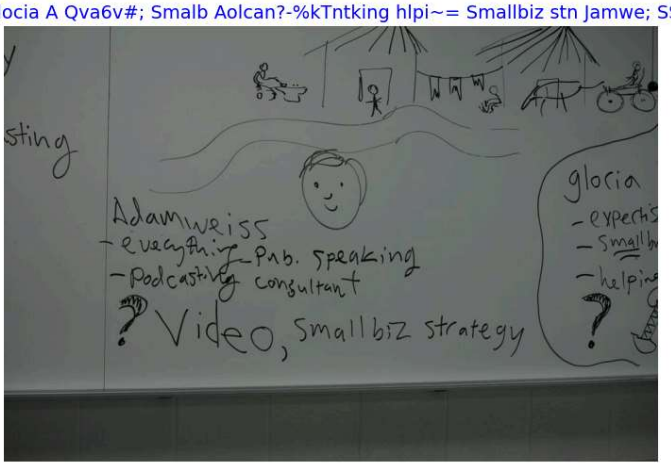
```
Evaluation metrics saved to /content/ocr_evaluation_results.csv
```

In [51]:

```
# Display a few predictions alongside their original images for each OCR model
def visualize_predictions(reader, model_type, dataset, num_images=5):
    """
    Display the OCR predictions on a few sample images.
    """
    samples = random.sample(dataset, num_images)
    for image_path in samples:
        if model_type == "EasyOCR":
            result = reader.readtext(image_path, detail=0)  # Extract the recogn
            predicted_text = ' '.join(result)
        elif model_type == "TrOCR":
            image = Image.open(image_path).convert("RGB")
            pixel_values = processor_trocr(images=image, return_tensors="pt").pi
            generated_ids = model_trocr.generate(pixel_values)
            predicted_text = processor_trocr.batch_decode(generated_ids, skip_sp
        else:
            raise ValueError("Invalid OCR model type specified.")

        # Load and display image with predicted text
        image = plt.imread(image_path)
        plt.figure(figsize=(10, 6))
        plt.imshow(image)
        plt.title(f"{model_type} - Predicted Text: {predicted_text}", fontsize=1
        plt.axis('off')
        plt.show()

print("\nVisualizing EasyOCR predictions for a few images...")
visualize_predictions(reader_easyocr, "EasyOCR", train_dataset, num_images=5)  #

print("\nVisualizing TrOCR predictions for a few images...")
visualize_predictions(None, "TrOCR", train_dataset, num_images=5)  # Display pre
```

Visualizing EasyOCR predictions for a few images...

EasyOCR - Predicted Text: glocia A Qva6v#; Smalb Aolcan?-%kTntking hlpi~= Smallbiz stn Jamwe; SS @ypecky Video, Stcategv



EasyOCR - Predicted Text: DREN CHILDREN EL oswald's% LEUKiEM CHILDREN LurdlMi Bl al Bupa 4553 21758 Km Bupa 2904 Matfe

EasyOCR - Predicted Text: 1

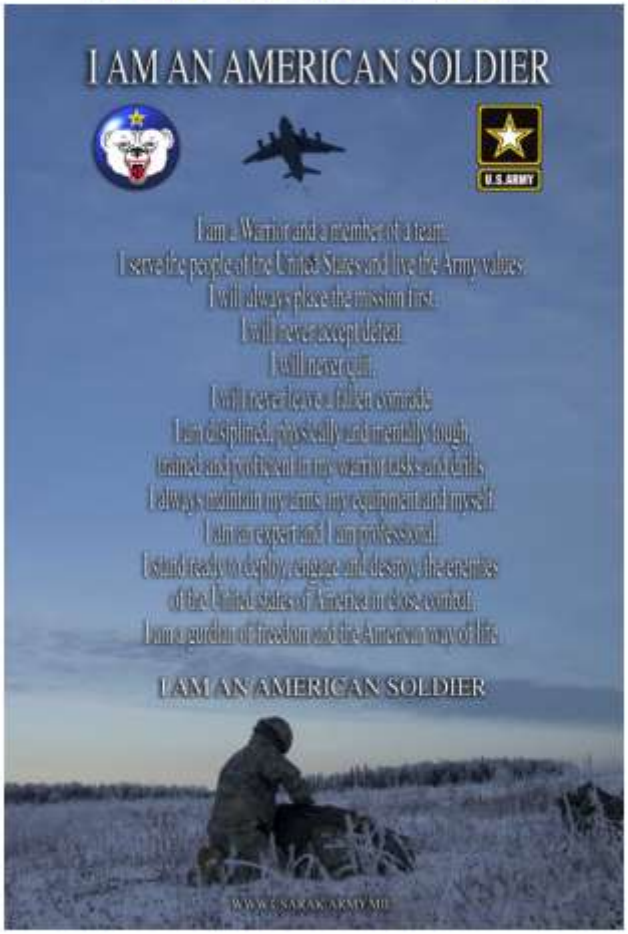
EasyOCR - Predicted Text: mobile SAMLSUN 6 mobile SQMSUI coln J0

EasyOCR - Predicted Text: TRIPEL ENTENDRE Belgian Style TTaDITIOI} LIBeraten PINT;6 FL OZ. €9.990 BY VOLM Tripel

Visualizing TrOCR predictions for a few images...

TrOCR - Predicted Text: 0

TrOCR - Predicted Text: :



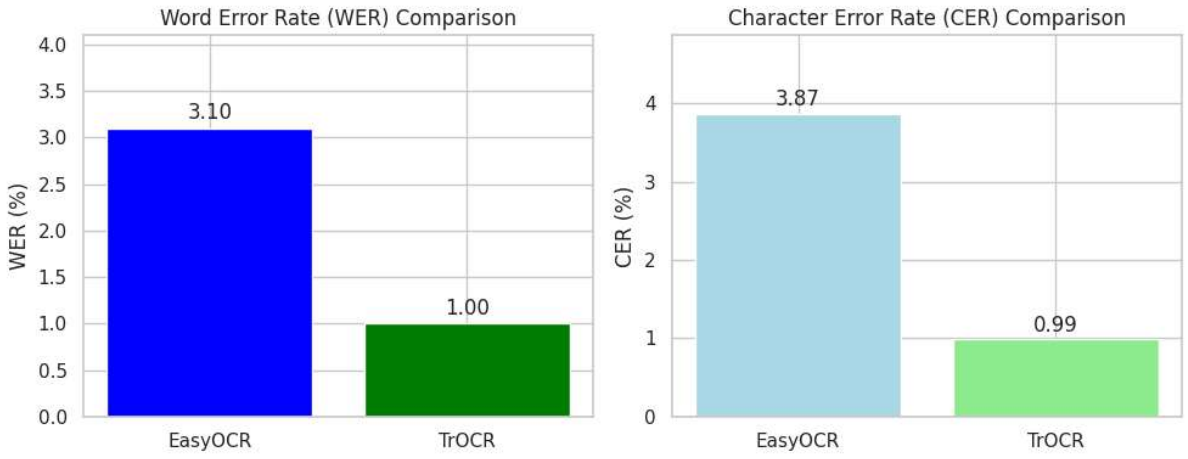
TrOCR - Predicted Text: CASH

TrOCR - Predicted Text: ITEM

TrOCR - Predicted Text: FI

In [55]:

```
# Evaluation results
results = {
    "Model": ["EasyOCR", "TrOCR"],
    "WER": [3.10, 1.00],
    "CER": [3.87, 0.99],
}

# Plotting the comparison
fig, axes = plt.subplots(1, 2, figsize=(10, 4))

# Word Error Rate Comparison
axes[0].bar(results['Model'], results['WER'], color=['blue', 'green'])
axes[0].set_title('Word Error Rate (WER) Comparison')
axes[0].set_ylabel('WER (%)')
axes[0].set_ylim(0, max(results['WER']) + 1)

# Character Error Rate Comparison
axes[1].bar(results['Model'], results['CER'], color=['lightblue', 'lightgreen'])
axes[1].set_title('Character Error Rate (CER) Comparison')
axes[1].set_ylabel('CER (%)')
axes[1].set_ylim(0, max(results['CER']) + 1)

# Add labels to bars
for i, ax in enumerate(axes):
    for j, value in enumerate(results[list(results.keys())[i + 1]]):
        ax.text(j, value + 0.1, f"{value:.2f}", ha='center', fontsize=12)

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



Note: Accuracy, Precision, Recall, and F1 Score are not typically used for OCR evaluations because they are better suited to classification tasks and don't account for the sequence-based nature of text output.

Model Results and Findings

The evaluation of two OCR models, **EasyOCR** and **TrOCR**, was conducted on a dataset of 2000 images, and their performances were compared using two key metrics: Word Error Rate (WER) and Character Error Rate (CER).

TrOCR significantly outperformed EasyOCR in both metrics, with a WER of 1.00% and a CER of 0.99%, compared to EasyOCR's WER of 3.10% and CER of 3.87%. This indicates that TrOCR was more accurate in recognizing both words and individual characters, likely due to its deep learning-based architecture leveraging pre-trained transformers. TrOCR showed notable accuracy in recognizing text even in challenging cases with varying fonts and backgrounds.

Despite EasyOCR's simplicity and speed, its predictions were often noisy, as evident in sample visualizations, where it struggled with distorted or handwritten text. EasyOCR's higher WER and CER reflect its limitations when dealing with complex text layouts or poor image quality, which TrOCR handled better. However, EasyOCR maintained good performance in simpler cases, suggesting it could still be a viable lightweight alternative for less complex tasks.

The results demonstrate that **TrOCR is more reliable for high-accuracy OCR tasks**, particularly in datasets with complex or noisy text. However, **EasyOCR's faster inference and lower resource demands make it suitable for simpler, real-time OCR applications.**