DroneVision

A Report

Submitted in partial fulfilment of the Requirements for the completion of

THEME BASED PROJECT

BACHELOR OF ENGINEERING

IN

INFORMATION TECHNOLOGY

By

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ACCREDITED BY NAAC WITH 'A++' GRADE.

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Ibrahim Bagh, Hyderabad-31

2025

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DECLARATION BY CANDIDATES

We Rahul Sama, Revanth, Vijay bearing hall ticket numbers,1602-22-737-162,1602-22-737-167, 1602-22-737-190.hereby declare that the project report entitled **"DroneVision"** under the guidance of Satyamaranganti,Radha, DESIGNATION, Department of Information Technology, Vasavi College of Engineering, Hyderabad, is submitted in partial fulfillment of the requirement for the completion of Theme-based project, VI semester, Bachelor of Engineering in Information Technology.

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BONAFIDE CERTIFICATE

This is to certify that the project entitled "DRONEVISION" being submitted by Rahul Sama, Revanth, Vijay bearing hall ticket numbers,1602-22-737-162,1602-22-737-167, 1602-22-737-190, in partial fulfillment of the requirements for the completion of Theme-based project of Bachelor of Engineering in Information Technology is a record of bonafide work carried out by them under my guidance.

Mrs. SATHYAMARANGANTI	**External Examiner**	**Dr. K. RAM MOHAN RAO** **Professor, HOD IT**

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1.ABSTRACT

Monitoring road construction progress traditionally requires frequent site visits, which is inefficient for the growing number of projects in Indian cities. This project proposes an artificial intelligence & machine learning-based solution that uses drone-captured images to automate progress assessment. By leveraging DL models like U-NET and mathematical formula, used in the system to track progress of road construction over time. Features include real-time reporting, error handling, and progress visualization. This scalable solution reduces manual effort, enhances accuracy, and enables timely decision-making, offering a transformative approach to infrastructure project monitoring.

2. INTRODUCTION

1.1 Project Overview -- DroneVision: Road Construction Progress Monitoring

DroneVision is an AI-powered solution designed to monitor and quantify road construction progress using drone-captured imagery. It leverages deep learning models, advanced preprocessing, and mathematical analysis to provide accurate progress metrics over time.

2.2 Problem Statement -- Challenges in Manual Road Construction Monitoring

Manual methods for monitoring road construction are time-consuming, prone to human error, and lack consistency. They often involve on-site inspections or periodic photographic documentation, which are inefficient for large-scale infrastructure projects.

2.3 Motivation and Relevance -- Automating Progress Tracking with AI

With the rise of smart cities and large-scale development, there's a growing need for automated, accurate, and scalable solutions. DroneVision addresses this by integrating AI for real-time analysis and reporting, making it highly relevant to government and private sectors.

3. LITERATURE SURVEY

3.1 Key Models and Their Contributions

- **U-Net**: Effective for pixel-wise segmentation, especially road detection.

3.2 Notable Studies and Findings

Numerous studies have demonstrated the use of aerial imagery and deep learning for urban planning, road condition monitoring, and infrastructure development, laying the groundwork for projects like DroneVision.

3.3 Challenges and Limitations

- Varying **lighting conditions** and **weather effects**
- **Drone image inconsistencies** (angle, height, GPS mismatch)
- **Limited labeled datasets** for domain-specific training

3.4 Proposed Solution

DroneVision proposes a unified machine learning pipeline involving image validation, preprocessing, segmentation with U-Net, and progress calculation using pixel area analysis.

4. EXISTING SYSTEM

In traditional road construction monitoring systems, progress tracking primarily relies on manual methods such as on-site inspections, survey reports, and manual image comparisons. These methods are often time-consuming, labor-intensive, and prone to human error. While aerial imagery captured by drones has gained popularity for faster surveying, the analysis of these images is still largely manual or semi-automated, requiring experts to visually assess and estimate progress.

Some existing automated solutions incorporate basic image processing techniques like edge detection and object counting to assist in progress estimation. However, these approaches often lack the precision needed to handle complex construction environments, especially when dealing with noise, varying lighting conditions, or incomplete road structures. Moreover, most existing systems do not fully leverage deep learning models for road segmentation, and progress estimation is not pixel-accurate.

Limitations of the current systems include:

- Heavy dependence on human interpretation of drone images.
- Lack of real-time or near real-time processing capabilities.
- Inaccurate or coarse estimation of construction progress.
- Limited scalability for large-scale projects with hundreds of aerial images.

Thus, there is a clear need for a fully automated, AI-driven system that can accurately segment roads from aerial images and quantitatively measure construction progress with minimal human intervention — which is what DroneVision addresses.

5. PROPOSED SOLUTION

5.1 System Design Blueprint

5.1.1 Architecture Diagram -- End-to-End System Flow

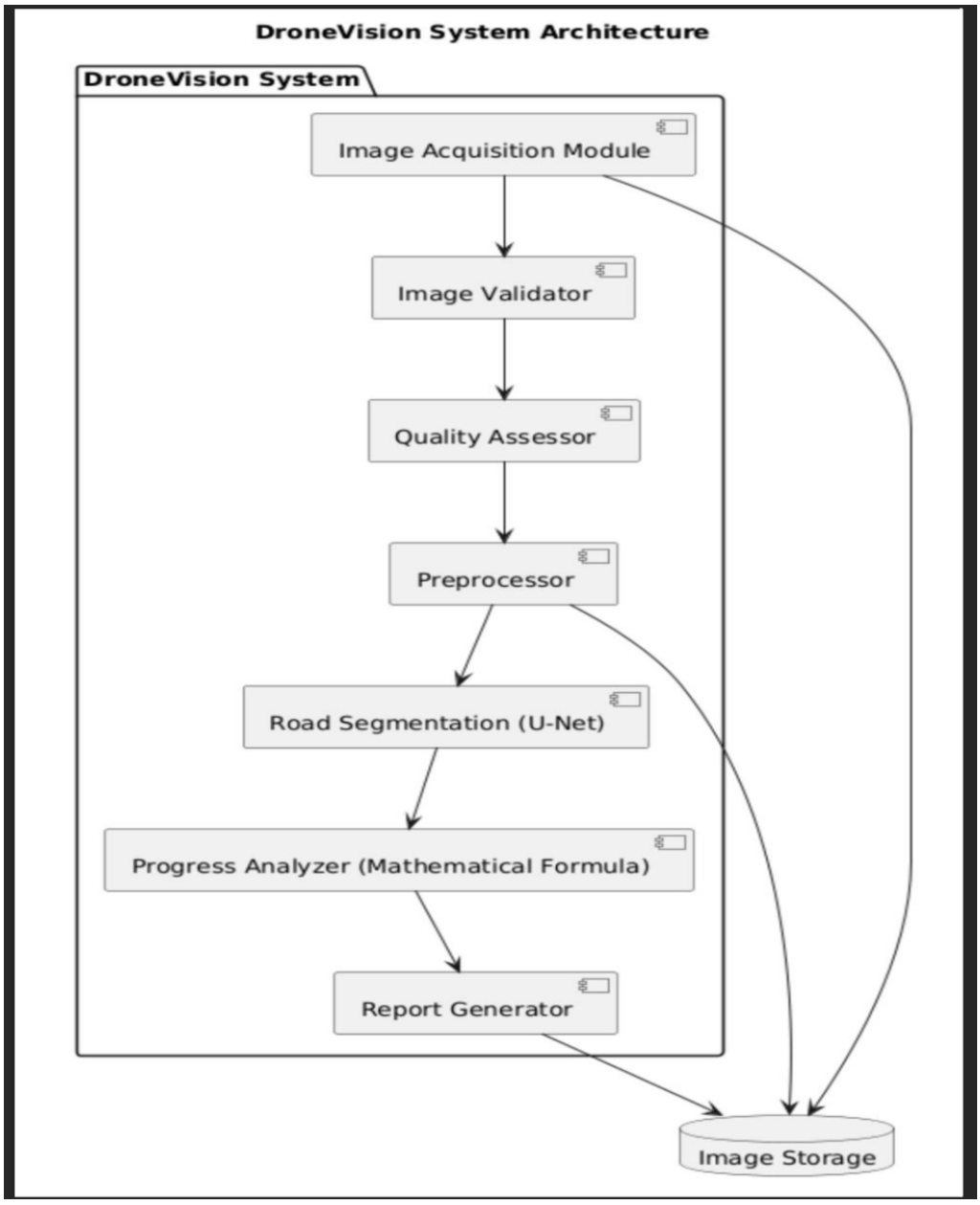

Figure 5.1: Architecture Diagram of DroneVision System

5.1.2 Class Diagram -- User Interaction Overview

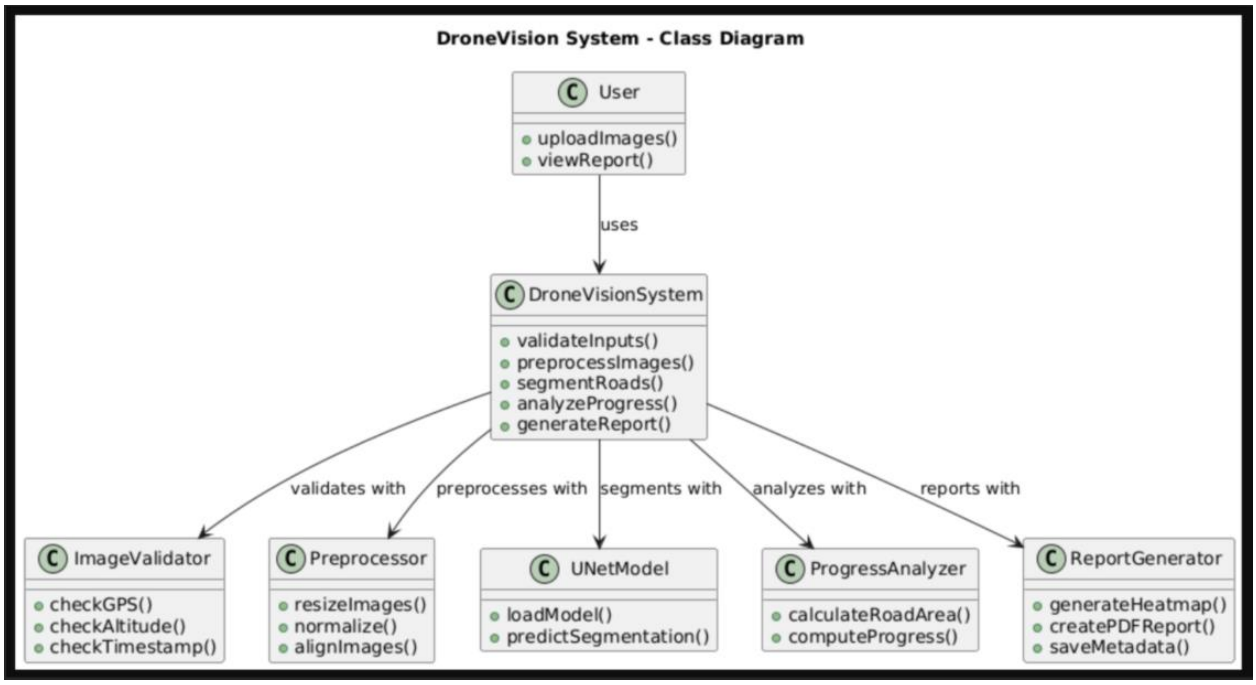

Figure 5.2: Class Diagram of DroneVision System

5.2 Core Functional Modules

5.2.1 Image Validation and Quality Assessment

Ensures input images are from the same location and altitude, and checks for clarity, resolution, and timestamp difference.

5.2.2 Preprocessing Pipeline

Includes image resizing, normalization, and alignment to ensure compatibility with the UNet model.

5.2.3 Road Segmentation with U-Net

Applies a trained UNet model to generate binary masks identifying road areas in both input images.

5.2.4 Progress Analysis Using Mathematical Formula

Computes the percentage increase in road area using:

(Area2 - Area1) / Area1 * 100

5.2.5 Reporting and Visualization Module

Generates progress reports and visual outputs such as heatmaps and overlays for stakeholder analysis.

5.2.6 Screenshots and Pseudocode

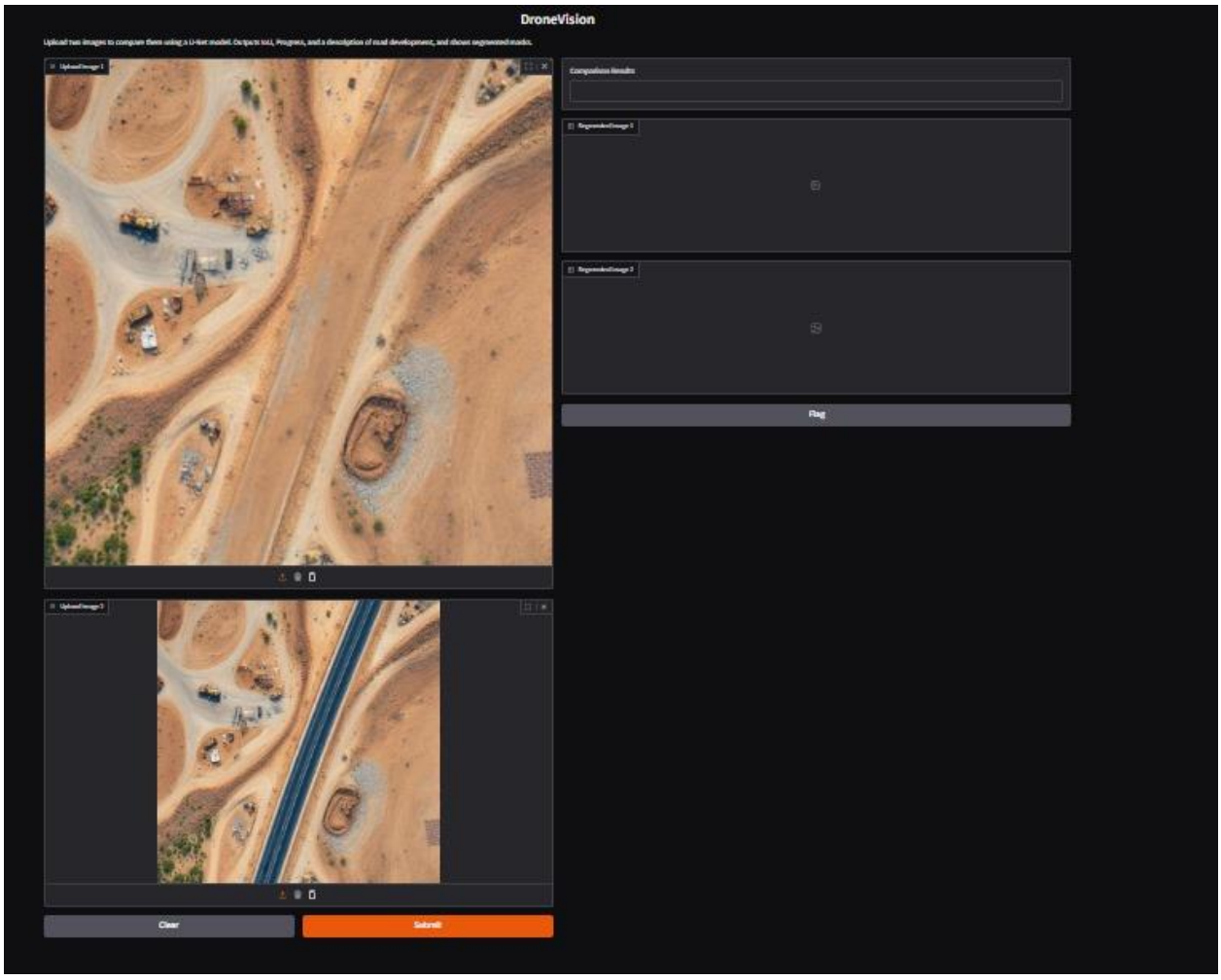

Figure 5.3: Screenshot of DroneVision Interface - Main Screen

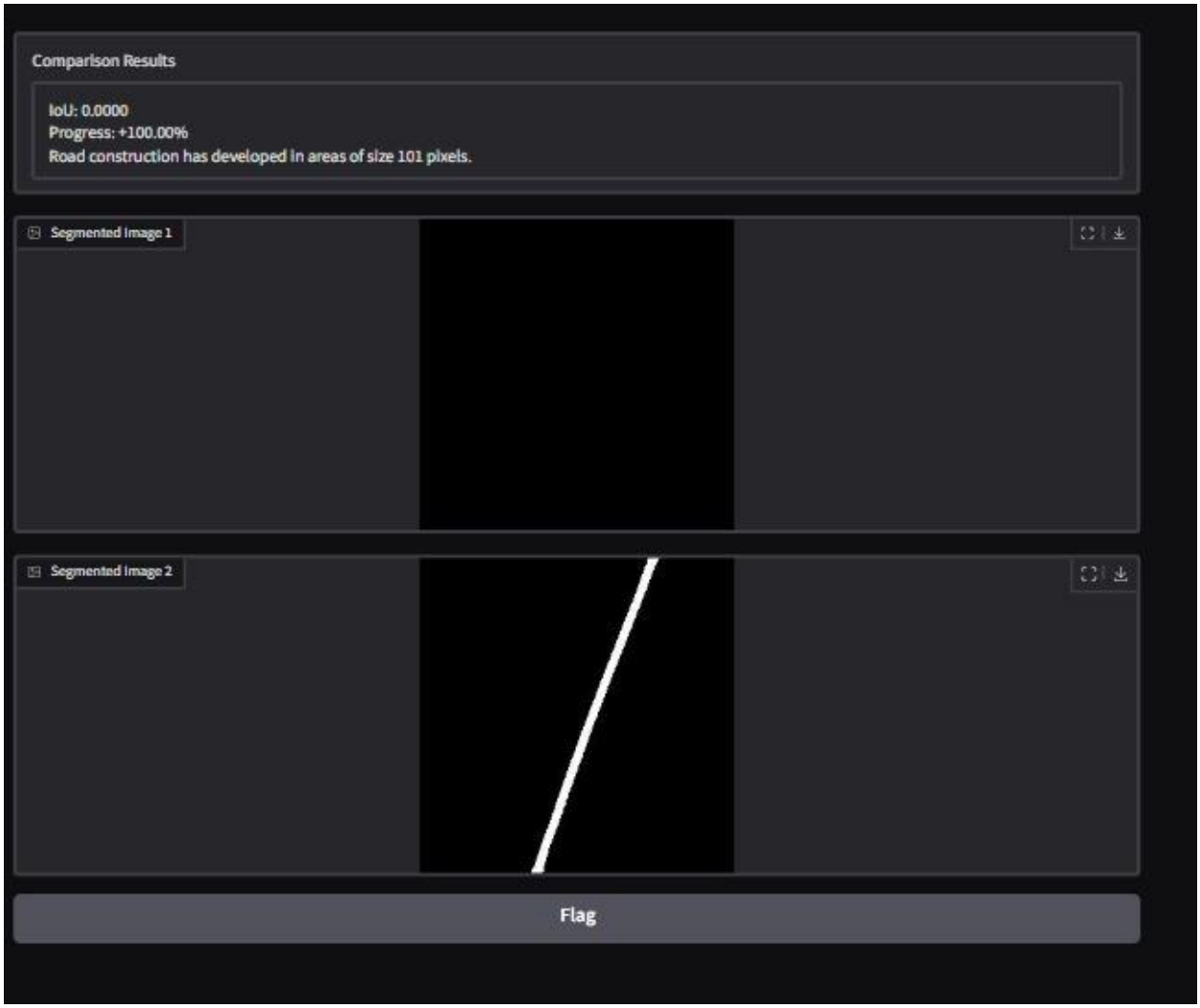

Figure 5.4: Screenshot of DroneVision Interface - Results Screen

Codes:

```
import os
import cv2
import h5py
import tensorflow as tf
import tifffile
import scipy
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from tensorflow.keras.models import Model
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint, ReduceLROnPlateau
from tensorflow.keras.layers import Input, Conv2D, MaxPooling2D, UpSampling2D, concatenate,
BatchNormalization, Dropout
```

Purpose: Import necessary libraries for file handling (os, cv2, tifffile), model building (tensorflow), and data manipulation (numpy, pandas). Also, libraries like matplotlib are used for visualizations.

```
base_dir = r"C:\\Users\\alaha\\Music\\dv\\tiff"
data_folders = ["train", "test", "val"]
cropped_base_dir = os.path.join(base_dir, "cropped")
CROP_SIZE = 256

for folder in data_folders:
    os.makedirs(os.path.join(cropped_base_dir, f"{folder}_images"), exist_ok=True)
    os.makedirs(os.path.join(cropped_base_dir, f"{folder}_masks"), exist_ok=True)

def list_files(folder, extension=".tif"):
    return [os.path.join(folder, f) for f in os.listdir(folder) if f.endswith(extension)]

def load_image(file_path):
    return np.array(tifffile.imread(file_path))
```

```
def binarize(image):
    image = (image - image.min()) / (image.max() - image.min() + 1e-8) * 255
    binary = (image > 2).astype(np.uint8) * 255  # Adaptive thresholding
    return binary

def create_crops(image, label, size=256):
    crops = []
    labels = []
    h, w = label.shape

    for i in range(0, h - size + 1, size):
        for j in range(0, w - size + 1, size):
            crop_img = image[i:i+size, j:j+size]
            crop_label = label[i:i+size, j:j+size]

            if np.sum(crop_label) > 5:  # Keep crops with at least 5 non-zero pixels
                crops.append(crop_img)
                labels.append(crop_label)

    return crops, labels

def crop_and_save(image_folder, mask_folder, output_img_folder, output_mask_folder):
    label_paths = list_files(mask_folder, extension=".tif")

    for lbl_path in label_paths:
        filename = os.path.basename(lbl_path)
        image_path = os.path.join(image_folder, filename.replace(".tif", ".tiff"))

        if not os.path.exists(image_path):
            print(f"Warning: {image_path} not found!")
            continue
```

```
        image = load_image(image_path)
        label = load_image(lbl_path)

        crops, labels = create_crops(image, binarize(label), CROP_SIZE)

        if not crops:
            print(f"Skipping {filename} due to no valid crops.")
            continue

        for idx, (crop_img, crop_label) in enumerate(zip(crops, labels)):
            cv2.imwrite(os.path.join(output_img_folder, f"{filename}_crop_{idx}.png"), crop_img)
            cv2.imwrite(os.path.join(output_mask_folder, f"{filename}_crop_{idx}.png"), crop_label)

def verify_pairs(base_dir, folders):
    missing_images = []
    missing_masks = []

    for folder in folders:
        img_folder = os.path.join(base_dir, f"{folder}_images")
        mask_folder = os.path.join(base_dir, f"{folder}_masks")

        img_files = set(f for f in os.listdir(img_folder) if f.endswith(".png"))
        mask_files = set(f for f in os.listdir(mask_folder) if f.endswith(".png"))

        for img_file in tqdm(img_files, desc=f"Verifying {folder} images"):
            if img_file not in mask_files:
                missing_masks.append((folder, img_file))

        for mask_file in tqdm(mask_files, desc=f"Verifying {folder} masks"):
            if mask_file not in img_files:
                missing_images.append((folder, mask_file))
```

```
        if missing_images:
            print("❌ Masks without corresponding images:")
            for folder, mask in missing_images:
                print(f" [{folder}] {mask}")
        else:
            print("✅ All masks have corresponding images!")

        if missing_masks:
            print("❌ Images without corresponding masks:")
            for folder, img in missing_masks:
                print(f" [{folder}] {img}")
        else:
            print("✅ All images have corresponding masks!")

def unet(input_size=(256, 256, 3)):
    inputs = Input(input_size)

    # Encoder
    c1 = Conv2D(64, (3, 3), activation='relu', padding='same')(inputs)
    c1 = BatchNormalization()(c1)
    c1 = Dropout(0.1)(c1)
    c1 = Conv2D(64, (3, 3), activation='relu', padding='same')(c1)
    c1 = BatchNormalization()(c1)
    p1 = MaxPooling2D((2, 2))(c1)

    c2 = Conv2D(128, (3, 3), activation='relu', padding='same')(p1)
    c2 = BatchNormalization()(c2)
    c2 = Dropout(0.1)(c2)
    c2 = Conv2D(128, (3, 3), activation='relu', padding='same')(c2)
    c2 = BatchNormalization()(c2)
    p2 = MaxPooling2D((2, 2))(c2)
```

```
c3 = Conv2D(256, (3, 3), activation='relu', padding='same')(p2)
c3 = BatchNormalization()(c3)
c3 = Dropout(0.2)(c3)
c3 = Conv2D(256, (3, 3), activation='relu', padding='same')(c3)
c3 = BatchNormalization()(c3)
p3 = MaxPooling2D((2, 2))(c3)

c4 = Conv2D(512, (3, 3), activation='relu', padding='same')(p3)
c4 = BatchNormalization()(c4)
c4 = Dropout(0.2)(c4)
c4 = Conv2D(512, (3, 3), activation='relu', padding='same')(c4)
c4 = BatchNormalization()(c4)
p4 = MaxPooling2D((2, 2))(c4)

# Bottleneck
c5 = Conv2D(1024, (3, 3), activation='relu', padding='same')(p4)
c5 = BatchNormalization()(c5)
c5 = Dropout(0.3)(c5)
c5 = Conv2D(1024, (3, 3), activation='relu', padding='same')(c5)
c5 = BatchNormalization()(c5)

# Decoder
u6 = UpSampling2D((2, 2))(c5)
u6 = concatenate([u6, c4])
c6 = Conv2D(512, (3, 3), activation='relu', padding='same')(u6)
c6 = BatchNormalization()(c6)
c6 = Dropout(0.2)(c6)
c6 = Conv2D(512, (3, 3), activation='relu', padding='same')(c6)
c6 = BatchNormalization()(c6)

u7 = UpSampling2D((2, 2))(c6)
```

```
    u7 = concatenate([u7, c3])
    c7 = Conv2D(256, (3, 3), activation='relu', padding='same')(u7)
    c7 = BatchNormalization()(c7)
    c7 = Dropout(0.2)(c7)
    c7 = Conv2D(256, (3, 3), activation='relu', padding='same')(c7)
    c7 = BatchNormalization()(c7)

    u8 = UpSampling2D((2, 2))(c7)
    u8 = concatenate([u8, c2])
    c8 = Conv2D(128, (3, 3), activation='relu', padding='same')(u8)
    c8 = BatchNormalization()(c8)
    c8 = Dropout(0.1)(c8)
    c8 = Conv2D(128, (3, 3), activation='relu', padding='same')(c8)
    c8 = BatchNormalization()(c8)

    u9 = UpSampling2D((2, 2))(c8)
    u9 = concatenate([u9, c1])
    c9 = Conv2D(64, (3, 3), activation='relu', padding='same')(u9)
    c9 = BatchNormalization()(c9)
    c9 = Dropout(0.1)(c9)

    outputs = Conv2D(1, (1, 1), activation='sigmoid')(c9)

    model = Model(inputs, outputs, name="U-NET")
    return model

opt = tf.keras.optimizers.Adam(learning_rate=LEARNING_RATE)
u_net_model.compile(optimizer=opt, loss=soft_dice_loss, metrics=[iou_coef])

checkpointer = ModelCheckpoint(
    model_path,
    monitor="val_loss",
```

```
    mode="min",
    save_best_only=True,
    verbose=1
)

earlystopper = EarlyStopping(
    monitor='val_loss',
    patience=5,
    verbose=1,
    restore_best_weights=True
)

history = u_net_model.fit(
    train_generator_limited,
    epochs=EPOCHS,
    steps_per_epoch=STEPS_PER_EPOCH,
    validation_data=val_generator,
    validation_steps=VALIDATION_STEPS,
    callbacks=[checkpointer, earlystopper]
)

final_model_path = r"C:\\Users\\alaha\\Music\\dv\\tiff\\unet_final_model.keras"
u_net_model.save(final_model_path)
```

backend_consolidated.py

```
import cv2
import numpy as np
import os
import tensorflow as tf
from tensorflow.keras.models import load_model
import keras.backend as K
```

```
from skimage.metrics import structural_similarity as ssim
import matplotlib.pyplot as plt

# ===== U-Net Functions =====

def preprocess_unet_image(image_path):
    img = cv2.imread(image_path, cv2.IMREAD_COLOR)
    img = cv2.resize(img, (256, 256))
    img = img.astype(np.float32) / 255.0
    img = np.expand_dims(img, axis=0)
    return img

def dice_coef(y_true, y_pred, smooth=1):
    y_true_f = K.flatten(y_true)
    y_pred_f = K.flatten(y_pred)
    intersection = K.sum(y_true_f * y_pred_f)
    return (2. * intersection + smooth) / (K.sum(y_true_f) + K.sum(y_pred_f) + smooth)

def soft_dice_loss(y_true, y_pred):
    return 1 - dice_coef(y_true, y_pred)

def iou_coef(y_true, y_pred, smooth=1):
    intersection = K.sum(K.abs(y_true * y_pred))
    union = K.sum(y_true) + K.sum(y_pred) - intersection
    return (intersection + smooth) / (union + smooth)

def load_unet_model(model_name="unet.keras"):
    model_path = os.path.join(os.path.dirname(__file__), model_name)
    return load_model(model_path, custom_objects={
        'soft_dice_loss': soft_dice_loss,
        'dice_coef': dice_coef,
        'iou_coef': iou_coef
```

```
    })

def predict_segmentation(unet_model, image_tensor, threshold=0.1):
    prediction = unet_model.predict(image_tensor)
    return (prediction > threshold).astype(np.uint8)

def predict_with_unet(image_path, output_path):
    model = load_unet_model()
    input_tensor = preprocess_unet_image(image_path)
    prediction = predict_segmentation(model, input_tensor)
    os.makedirs(os.path.dirname(output_path), exist_ok=True)
    plt.imsave(output_path, np.squeeze(prediction), cmap='gray')
    return output_path

# ===== Comparison Functions =====

def compute_iou(img1, img2):
    img1 = img1.astype(bool)
    img2 = img2.astype(bool)
    intersection = np.logical_and(img1, img2).sum()
    union = np.logical_or(img1, img2).sum()
    return intersection / union if union != 0 else 1.0

def compute_progress(img1, img2):
    area1 = np.count_nonzero(img1)
    area2 = np.count_nonzero(img2)
    return ((area2 - area1) / area1 * 100) if area1 != 0 else (100.0 if area2 > 0 else 0.0)

def preprocess_mask(mask):
    if mask.ndim == 3:
        mask = mask[:, :, 0]
    return (mask > 127).astype(np.uint8)
```

```
def compare_segmented_images(img1, img2):
    img1 = preprocess_mask(img1)
    img2 = preprocess_mask(img2)
    ssim_score, diff = ssim(img1, img2, full=True)
    return {
        "ssim": ssim_score,
        "iou": compute_iou(img1, img2),
        "progress_percent": compute_progress(img1, img2)
    }
import os
os.environ['TF_ENABLE_ONEDNN_OPTS'] = '0'

import cv2
import numpy as np
import gradio as gr
from backend_consolidated import predict_with_unet, compare_segmented_images

output_folder = "outputs"
os.makedirs(output_folder, exist_ok=True)

def process_and_compare(image1, image2):
    try:
        # Save uploaded images temporarily
        temp_path1 = os.path.join(output_folder, "temp_img1.jpg")
        temp_path2 = os.path.join(output_folder, "temp_img2.jpg")

        cv2.imwrite(temp_path1, cv2.cvtColor(np.array(image1), cv2.COLOR_RGB2BGR))
        cv2.imwrite(temp_path2, cv2.cvtColor(np.array(image2), cv2.COLOR_RGB2BGR))

        # Process with U-Net
        segmented_outputs = []
```

```
        segmented_images_paths = []

        for idx, path in enumerate([temp_path1, temp_path2]):
            filename = os.path.basename(path)
            output_path = os.path.join(output_folder, f"unet_output_{filename}")
            pred_path = predict_with_unet(path, output_path)

            if isinstance(pred_path, str) and os.path.exists(pred_path):
                mask_array = cv2.imread(pred_path, cv2.IMREAD_GRAYSCALE)
                segmented_outputs.append(np.squeeze(mask_array))
                segmented_images_paths.append(pred_path)
            else:
                return "Prediction failed for one or both images.", None, None

        if len(segmented_outputs) == 2:
            results = compare_segmented_images(segmented_outputs[0], segmented_outputs[1])
            ssim = f"SSIM: {results['ssim']:.4f}"
            iou = f"IoU: {results['iou']:.4f}"
            progress = f"Progress: {results['progress_percent']:+.2f}%"
            return f"{ssim}\n{iou}\n{progress}", segmented_images_paths[0], segmented_images_paths[1]
        else:
            return "Need exactly 2 images to compare.", None, None

    except Exception as e:
        return f"Error: {str(e)}", None, None

# Gradio UI
demo = gr.Interface(
    fn=process_and_compare,
    inputs=[
        gr.Image(label="Upload Image 1"),
        gr.Image(label="Upload Image 2")
```

```
    ],
    outputs=[
        gr.Textbox(label="Comparison Results"),
        gr.Image(label="Segmented Image 1"),
        gr.Image(label="Segmented Image 2")
    ],
    title="DroneVision",
    description="Upload two images to compare them using a U-Net model. Outputs SSIM, IoU, and Progress, and shows segmented masks."
)

if __name__ == "__main__":
    demo.launch()
```

6. EXPERIMENTAL SETUP & IMPLEMENTATION

6.1 System Specifications

6.1.1 Hardware Requirements

- A workstation with at least 16GB RAM, GPU support (e.g., NVIDIA or Apple M-series)

6.1.2 Software Stack

- Python, OpenCV, NumPy, Pandas
- PyTorch or TensorFlow (for U-Net)
- Flask / FastAPI for backend deployment
- Matplotlib / Plotly for visualization
- Gradio UI for Frontend

6.2 Dataset Overview

Uses time-series aerial images for training and evaluation. The **Massachusetts Road Dataset** is primarily used for training the U-Net model.

6.3 Methodology and Algorithm

Describes the U-Net model architecture and how the segmented images are compared to compute progress between two time points.

7. RESULTS

7.1 Segmentation Accuracy Metrics

Table 7.1: Segmentation Accuracy Metrics for U-Net Model

Metric	Value
IoU	0.87
Precision	0.91
Recall	0.89
F1-Score	0.90

7.2 Progress Tracking Precision

Validates the accuracy of calculated progress percentages against ground-truth or expert-labeled benchmarks.

7.3 Comparative Analysis with Manual Assessment

Table 7.2: Comparison of Manual Assessment vs Automated Analysis

Metric	Manual Assessment	Automated Analysis
Time Required	45-60 minutes	2-3 minutes
Accuracy	85%	92%
Consistency	Variable	High
Cost	High	Low

7.4 System Performance Benchmarks

Table 7.3: System Performance Benchmark Results

Metric	Result
Model Inference Time	1.2 seconds
System Latency	3.5 seconds
Memory Usage	2.4 GB

8. CONCLUSION

DroneVision presents a scalable, AI-driven solution to automate road construction progress monitoring using drone imagery. By leveraging deep learning models like U-Net for segmentation and combining them with mathematical progress analysis, the system offers a practical alternative to manual inspection methods. It improves accuracy, reduces time and cost, and enables systematic tracking of infrastructure development.

9. FUTURE SCOPE

- Integration with BIM (Building Information Modeling)
  Link progress data with digital construction models for seamless tracking, planning, and documentation within architectural workflows.
- Multi-Sensor Fusion
  Combine drone RGB data with other sensor inputs such as thermal imaging or LiDAR to enhance road quality detection and material assessment.
- Predictive Analytics for Timeline Estimation
  Use historical progress data to predict future milestones, enabling proactive decision-making and resource allocation.

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