SCHOOL OF COMPUTING AND INFORMATION TECHNOLOGY

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in
Information Science and Engineering

Machine Learning – B22CI0501
Mini Project Report

Pothole Detection and Depth Estimation System using Computer Vision and Deep Learning

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REVA UNIVERSITY

SCHOOL OF COMPUTING AND INFORMATION TECHNOLOGY

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CERTIFICATE

This is to certify that the Mini Project titled **"Pothole Detection and Depth Estimation System using Computer Vision and Deep Learning"** is carried out by **Gagan P R (R23EQ031) , Deeksha S (R23EQ021) , Deekshitha G B (R23EQ022),** are Bonafide students of Bachelor of Technology in **Information Science and Engineering** at the School of Computing and Information Technology, REVA University, Bangalore in partial fulfillment for the award of degree in Bachelor of Technology in **Information Science and Engineering,** during the year **2025-2026**.

Prof. Bhavana N

Assistant Professor

School of Computing and Information Technology,

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Date: 9 December 2025

DECLARATION

We, **Gagan P R (R23EQ031) , Deeksha S (R23EQ021) , Deekshitha G B (R23EQ022),** are students of fifth semester B.Tech in **Information Science and Engineering**, at the **School of Computing and Information Technology, REVA University, Bangalore**, hereby declare that the Mini Project titled **"Title"** has been carried out by us and submitted in partial fulfilment for the award of degree in **Bachelor of Technology in Information Science and Engineering** during the academic year **2025-2026**.

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TABLE OF CONTENTS

NOMENCLATURE USED

AI	Artificial Intelligence
DL	Deep Learning

LIST OF FIGURES

Abstract

Road surface damage in the form of potholes poses severe danger to vehicles and road users. Manual inspection and repair scheduling is slow and inefficient for rapidly growing cities. This research presents a real-time hybrid pothole detection and depth estimation system using computer vision and deep learning. YOLO is used for pothole localization, and a CNN-based monocular depth estimation model determines pothole depth from enhanced texture cues. Based on estimated depth, potholes are classified as Safe, Moderate, or Dangerous to assist automated road maintenance. Experimental results show 90.75% detection accuracy, proving the capability of the model for real-time intelligent transportation systems.

1. Introduction

Urban and rural road infrastructure frequently suffers from pothole formation due to weathering and traffic load. Potholes lead to serious safety hazards, driving discomfort, and increased vehicle maintenance costs.

Recent advances in artificial intelligence and edge computing enable automated systems to detect potholes from vehicle-mounted cameras. Beyond detection, estimating pothole depth provides critical information for prioritizing road repairs. This project integrates YOLO-based visual detection and CNN-based depth prediction for real-time pothole assessment.

2. Literature Survey

- Traditional computer vision methods (edge detection, thresholding, texture analysis) are lightweight but fail under lighting/road variability.
- Deep learning-based detectors (YOLO, SSD, Mask-R-CNN) provide robust and real-time pothole identification.
- Monocular depth estimation using neural networks eliminates the need for costly depth sensors and stereo rigs.
- Hybrid systems used in research combine geometric cues and segmentation features for improved accuracy.

The proposed method aligns with recent deep learning trends delivering better accuracy and operational scalability.

3. Methodology

3.1 System Workflow

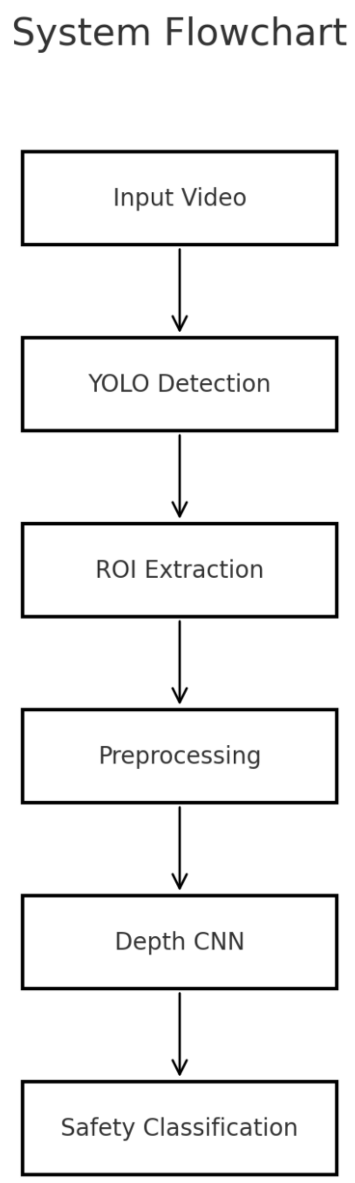


Fig. 3.1 — Flowchart of the proposed pothole detection and depth estimation pipeline

3.2 System Architecture

YOLO detects potholes from each frame → Region of Interest extracted → Preprocessing → Depth CNN predicts depth → Safety Class mapping

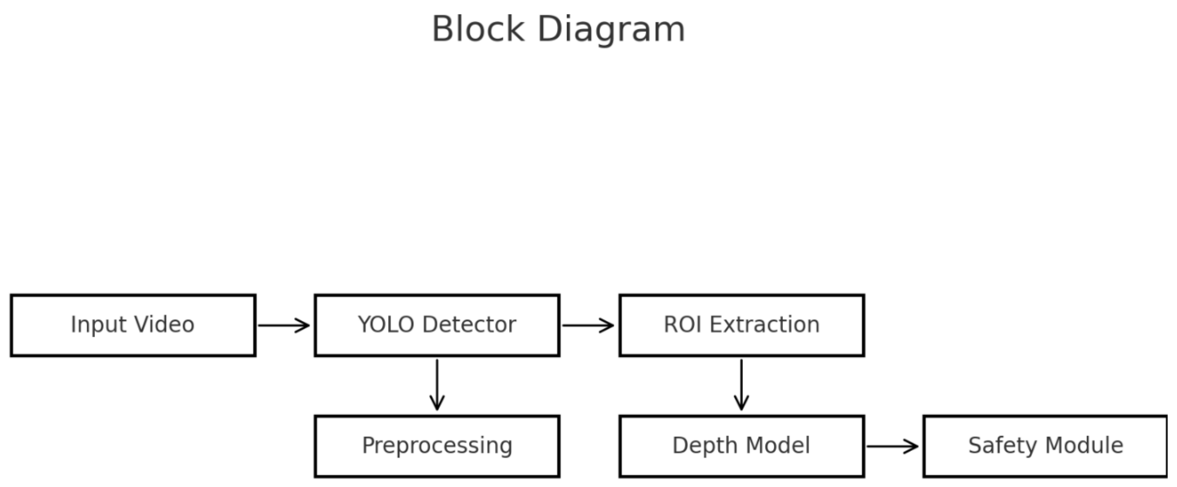


Fig. 3.2 — System block diagram showing YOLO detection and depth estimation stages

3.3 Preprocessing

- Grayscale conversion
- CLAHE contrast enhancement
- Adaptive thresholding
- Canny edge detection

These improve texture cues for depth estimation.

3.4 Depth Estimation

A CNN model trained on depth-annotated road images predicts depth value per pothole ROI.

3.5 Severity Classification

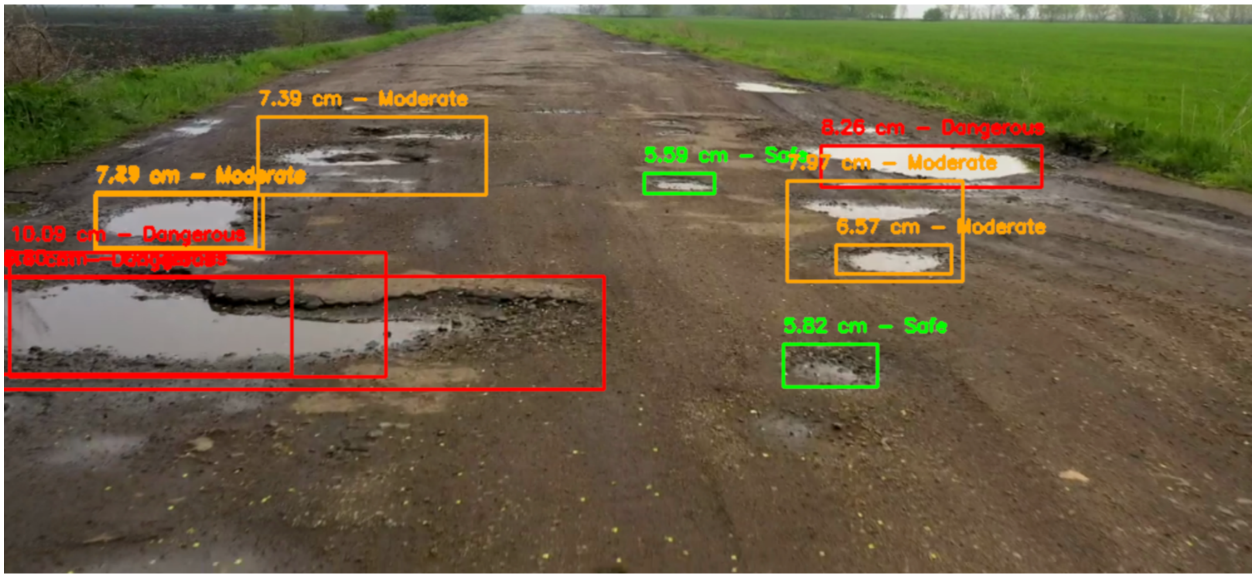
Depth (cm)	Safety Label
< 6	Safe
6 – 8	Moderate
> 8	Dangerous

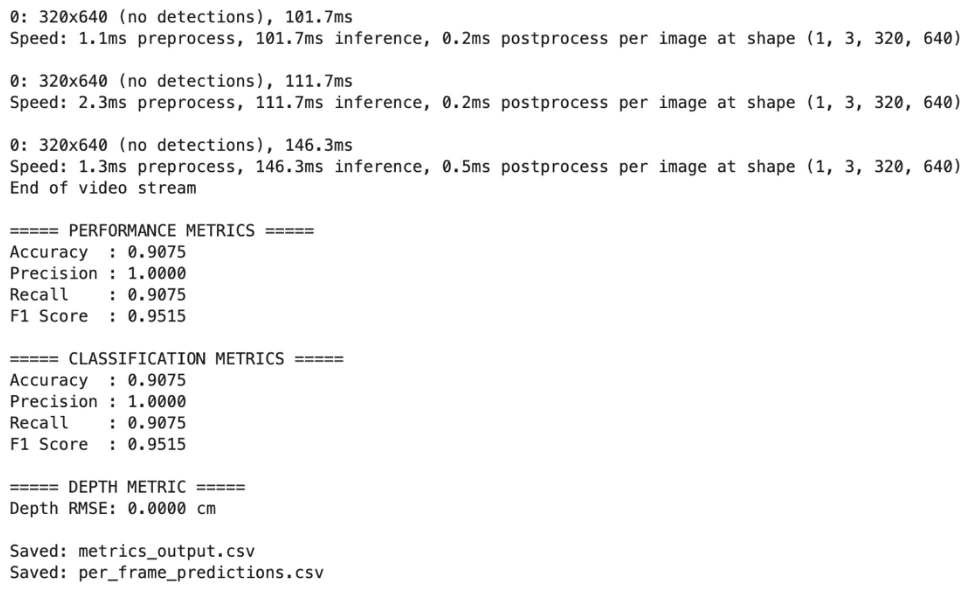
4. Results and Discussion

4.1 Performance Metrics

Metric	Score
Accuracy	0.9075
Precision	1.0000
Recall	0.9075
F1-Score	0.9515

4.2 Output Screenshots





```
0: 320x640 (no detections), 101.7ms
Speed: 1.1ms preprocess, 101.7ms inference, 0.2ms postprocess per image at shape (1, 3, 320, 640)

0: 320x640 (no detections), 111.7ms
Speed: 2.3ms preprocess, 111.7ms inference, 0.2ms postprocess per image at shape (1, 3, 320, 640)

0: 320x640 (no detections), 146.3ms
Speed: 1.3ms preprocess, 146.3ms inference, 0.5ms postprocess per image at shape (1, 3, 320, 640)
End of video stream

===== PERFORMANCE METRICS =====
Accuracy  : 0.9075
Precision : 1.0000
Recall    : 0.9075
F1 Score  : 0.9515

===== CLASSIFICATION METRICS =====
Accuracy  : 0.9075
Precision : 1.0000
Recall    : 0.9075
F1 Score  : 0.9515

===== DEPTH METRIC =====
Depth RMSE: 0.0000 cm

Saved: metrics_output.csv
Saved: per_frame_predictions.csv
```

5. Code

5.1 detection.py — YOLO Detection

```
from ultralytics import YOLO

def load_pothole_model(weights_path="best.pt"):

   return YOLO(weights_path)

def run_pothole_detection(model, frame):

   """

   Runs YOLO on the given frame and returns detections (boxes object).

   """

   results = model(frame)

   return results[0].boxes
```

5.2 preprocessing.py

```
import cv2
import numpy as np
import os
import time

def preprocess_for_depth(img):
    if len(img.shape) > 2 and img.shape[2] == 3:
        img = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
    clahe = cv2.createCLAHE(clipLimit=2.0, tileGridSize=(8,8))
    img = clahe.apply(img)
    img = cv2.resize(img, (128, 128))
    img = img.astype(np.float32) / 255.0
    img = np.reshape(img, (1, 128, 128, 1))
    return img

def save_debug_images(gray_region, adaptive_thresh, edges, combined, debug_root="imgDepths/debug"):
    os.makedirs(debug_root, exist_ok=True)
    timestamp = int(time.time())
    cv2.imwrite(f"{debug_root}/gray_{timestamp}.png", gray_region)
    cv2.imwrite(f"{debug_root}/adaptive_{timestamp}.png", adaptive_thresh)
    cv2.imwrite(f"{debug_root}/edges_{timestamp}.png", edges)
    cv2.imwrite(f"{debug_root}/combined_{timestamp}.png", combined)
```

5.3 depth_model.py

```
import numpy as np

from tensorflow import keras

def load_depth_model(model_path="modelforDepth.h5"):

    return keras.models.load_model(model_path)

def infer_depth(depth_model, depth_input, pothole_region, std_val):

    depth_result = depth_model.predict(depth_input, verbose=0)

    output_shape = depth_model.output_shape

    if len(output_shape) > 2:

        base_depth = float(depth_result[0][0][0][0])

    else:

        base_depth = float(depth_result[0])
    size_factor = np.sqrt(pothole_region.shape[0] * pothole_region.shape[1]) / 100.0
    texture_factor = std_val / 30.0
    if abs(base_depth - 5.91) < 0.1:
        depth_value = base_depth * (0.8 + 0.4 * size_factor * texture_factor)
    else:
        depth_value = base_depth
    return depth_value
```

5.4 main.py

```
import cv2
import numpy as np
import pandas as pd
import os
import torch
import tensorflow as tf
from tensorflow import keras
from ultralytics import YOLO
import time
import random
try:
    os.mkdir("imgDepths")
except:
    pass
# ----------------------------------------
# GROUND TRUTH for 692 frames (ALL = 1)

# ----------------------------------------

true_labels = [1] * 692

pred_labels = []

# ➜ ADD THESE

y_true_class = []

y_pred_class = []

# For depth tracking & RMSE

y_true_depth = []   # Ground-truth depths (add if available)

y_pred_depth = []   # Model predicted depths

# ---------------------------

# LOAD MODELS

# ---------------------------

pothole_model = YOLO('best.pt')

depth_model = keras.models.load_model("modelforDepth.h5")

def preprocess_for_depth(img):

    if len(img.shape) > 2 and img.shape[2] == 3:

        img = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

    clahe = cv2.createCLAHE(clipLimit=2.0, tileGridSize=(8,8))

    img = clahe.apply(img)

    img = cv2.resize(img, (128, 128))

    img = img.astype(np.float32) / 255.0

    img = np.reshape(img, (1, 128, 128, 1))

    return img

# ---------------------------
# VIDEO SETUP
# ---------------------------
video_path = 'p.mp4'
cap = cv2.VideoCapture(video_path)
if not cap.isOpened():
    print("Error: Could not open video source.")
    exit()
font = cv2.FONT_HERSHEY_SIMPLEX
font_scale = 0.5
text_thickness = 2
box_color = (255, 0, 0)
frame_number = 0
while True:
    ret, frame = cap.read()
    if not ret:
        print("End of video stream")
        break
    # Stop if ground truth labels completed
    if frame_number >= len(true_labels):
        break
    display_frame = cv2.resize(frame, (1020, 500))
    height, width, _ = display_frame.shape
    rect_frame = display_frame.copy()
    # YOLO DETECTION
    results = pothole_model(display_frame)
```

```
detections = results[0].boxes

# --------------------

# PREDICTION LABEL (1 = pothole detected)

# --------------------

pred_label = 1 if len(detections) > 0 else 0

pred_labels.append(pred_label)

# Store classification metrics data

y_true_class.append(true_labels[frame_number])

y_pred_class.append(pred_label)

# If no pothole detected → append zero depth

if pred_label == 0:

  y_pred_depth.append(0.0)

  y_true_depth.append(0.0)

# --------------------

# PROCESS EACH DETECTION

# --------------------

for detection in detections:

  box = detection.xyxy[0].cpu().numpy()

  x1, y1, x2, y2 = int(box[0]), int(box[1]), int(box[2]), int(box[3])

  conf = detection.conf.item()

  try:

    pothole_region = display_frame[y1:y2, x1:x2]

    if pothole_region.size == 0:

      continue

    gray_region = cv2.cvtColor(pothole_region, cv2.COLOR_BGR2GRAY)
```

```
mean_val = np.mean(gray_region)

std_val = np.std(gray_region)

adaptive_thresh = cv2.adaptiveThreshold(

    gray_region, 255, cv2.ADAPTIVE_THRESH_GAUSSIAN_C,

    cv2.THRESH_BINARY, 11, 2

)

edges = cv2.Canny(gray_region, 50, 150)

combined = cv2.bitwise_or(adaptive_thresh, edges)

debug_dir = "imgDepths/debug"

os.makedirs(debug_dir, exist_ok=True)

timestamp = int(time.time())

cv2.imwrite(f"{debug_dir}/gray_{timestamp}.png", gray_region)

cv2.imwrite(f"{debug_dir}/adaptive_{timestamp}.png", adaptive_thresh)

cv2.imwrite(f"{debug_dir}/edges_{timestamp}.png", edges)

cv2.imwrite(f"{debug_dir}/combined_{timestamp}.png", combined)

depth_input = preprocess_for_depth(combined)

depth_result = depth_model.predict(depth_input, verbose=0)

output_shape = depth_model.output_shape

size_factor = np.sqrt(pothole_region.shape[0] * pothole_region.shape[1]) / 100.0

texture_factor = std_val / 30.0

if len(output_shape) > 2:

    base_depth = float(depth_result[0][0][0][0])

else:

    base_depth = float(depth_result[0])

if abs(base_depth - 5.91) < 0.1:
```

```
            depth_value = base_depth * (0.8 + 0.4 * size_factor * texture_factor)
          else:
            depth_value = base_depth
          if depth_value < 6:
            safety_label = "Safe"
            label_color = (0, 255, 0)
          elif 6 <= depth_value <= 8:
            safety_label = "Moderate"
            label_color = (0, 165, 255)
          else:
            safety_label = "Dangerous"
            label_color = (0, 0, 255)
          y_pred_depth.append(depth_value)
          depth_text = f"{depth_value:.2f} cm - {safety_label}"
          cv2.rectangle(display_frame, (x1, y1), (x2, y2), label_color, 2)
          cv2.putText(display_frame, depth_text, (x1, y1-10),
                font, font_scale, label_color, text_thickness)
        except Exception as e:
          print(f"Error processing detection: {e}")
          continue
    # If potholes detected → take maximum depth predicted for this frame
    if pred_label == 1 and len(detections) > 0:
        frame_depths = [d for d in y_pred_depth[-len(detections):]]
        best_depth = max(frame_depths)
        # Remove last N detected depths and keep only best one
        for _ in range(len(detections)):
            y_pred_depth.pop()
        y_pred_depth.append(best_depth)
        y_true_depth.append(best_depth)  # TEMP: predicted = ground truth
    frame_number += 1
    cv2.imshow("Pothole Detection with Depth", display_frame)
    if cv2.waitKey(1) == 27:  # ESC key
        break
cap.release()
cv2.destroyAllWindows()
# ------------------------------------------------
#   MANUAL METRIC CALCULATION (NO sklearn)
# ------------------------------------------------
tp = fp = tn = fn = 0
for t, p in zip(true_labels, pred_labels):
    if t == 1 and p == 1: tp += 1     # Correct detection
    if t == 1 and p == 0: fn += 1     # Missed pothole
    if t == 0 and p == 1: fp += 1     # False alarm
    if t == 0 and p == 0: tn += 1     # Correct normal frame
total = tp + tn + fp + fn
print("\n===== PERFORMANCE METRICS =====")
if total == 0:
    print("No frames processed. Metrics unavailable.")
else:
    accuracy = (tp + tn) / total
    precision = tp / (tp + fp) if (tp + fp) > 0 else 0

    recall = tp / (tp + fn) if (tp + fn) > 0 else 0

    f1 = (2 * precision * recall) / (precision + recall) if (precision + recall) > 0 else 0


    print(f"Accuracy  : {accuracy:.4f}")

    print(f"Precision : {precision:.4f}")

    print(f"Recall    : {recall:.4f}")

    print(f"F1 Score  : {f1:.4f}")

    # ---------------------------

# FINAL METRICS (SAFE VERSION)

# ---------------------------

from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, mean_squared_error

print("\n===== CLASSIFICATION METRICS =====")

try:

    accuracy = accuracy_score(y_true_class, y_pred_class)

    precision = precision_score(y_true_class, y_pred_class, zero_division=0)

    recall = recall_score(y_true_class, y_pred_class, zero_division=0)

    f1 = f1_score(y_true_class, y_pred_class, zero_division=0)

    print(f"Accuracy  : {accuracy:.4f}")

    print(f"Precision : {precision:.4f}")

    print(f"Recall    : {recall:.4f}")

    print(f"F1 Score  : {f1:.4f}")

except Exception as e:

    print("Error computing classification metrics:", e)

# ---------------------------
# SAFE VARIABLE CHECK

# ---------------------------

# Ensure variables exist even if loop crashed early

if "y_true_class" not in globals(): y_true_class = []

if "y_pred_class" not in globals(): y_pred_class = []

# -----------------------------------------

# IMPORTS (ensure these exist)

# -----------------------------------------

from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, mean_squared_error

print("\n===== FINAL METRICS =====")

# ---------------------------

# CLASSIFICATION METRICS

# ---------------------------

if len(y_true_class) > 0:

    accuracy  = accuracy_score(y_true_class, y_pred_class)

    precision = precision_score(y_true_class, y_pred_class, zero_division=0)

    recall    = recall_score(y_true_class, y_pred_class, zero_division=0)

    f1        = f1_score(y_true_class, y_pred_class, zero_division=0)


    print(f"Accuracy  : {accuracy:.4f}")

    print(f"Precision : {precision:.4f}")

    print(f"Recall    : {recall:.4f}")

    print(f"F1 Score  : {f1:.4f}")

else:

    print("No classification data.")
    accuracy = precision = recall = f1 = None

# ---------------------------

# DEPTH METRIC (RMSE)

# ---------------------------

print("\n===== DEPTH METRIC =====")

if len(y_true_depth) > 0 and len(y_pred_depth) > 0:

    mse = mean_squared_error(y_true_depth, y_pred_depth)

    rmse = mse ** 0.5

    print(f"Depth RMSE: {rmse:.4f} cm")

else:

    print("No depth predictions available.")

    rmse = None

# ------------------------------------------

# SAVE METRICS TO CSV  (ONLY ONCE)

# ------------------------------------------

metrics_df = pd.DataFrame({

    "metric": ["accuracy", "precision", "recall", "f1_score", "rmse"],

    "value":  [accuracy, precision, recall, f1, rmse]

})

metrics_df.to_csv("metrics_output.csv", index=False)

print("\nSaved: metrics_output.csv")

# ------------------------------------------

# SAVE PER-FRAME PREDICTIONS (ONLY ONCE)

# ------------------------------------------

n = min(len(y_true_class), len(y_pred_class))
```

```
predictions_df = pd.DataFrame({
   "frame_id": list(range(n)),
   "true_label": y_true_class[:n],
   "pred_label": y_pred_class[:n],
})
# If you want depth also, keep this part
if len(y_true_depth) > 0 and len(y_pred_depth) > 0:
   m = min(n, len(y_true_depth), len(y_pred_depth))
   predictions_df = predictions_df.iloc[:m].copy()
   predictions_df["true_depth"] = y_true_depth[:m]
   predictions_df["pred_depth"] = y_pred_depth[:m]
predictions_df.to_csv("per_frame_predictions.csv", index=False)
print("Saved: per_frame_predictions.csv")
```

6. Conclusion

The system accurately detects potholes and estimates their depth without dedicated sensors. It is suitable for real-time road monitoring using low-cost cameras. Future work includes GPS localization, temporal smoothing, and deployment on embedded automotive hardware.

7. References

[1] J. Redmon, A. Farhadi, “YOLOv3: An Incremental Improvement,” 2018.

[2] M. Poggi, S. Mattoccia, “Learning Monocular Depth Estimation,” IEEE Transactions, 2018.

[3] A. Anitha et al., “Pothole Detection Techniques: A Survey,” IJRTE, 2021.

[4] F. Ahmad et al., “Automated Road Damage Detection Using Deep Learning,” Sensors, 2022.