Automated Road Surface Layers Analysis using Multi-Method Image Processing Approach

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ABSTRACT

Road infrastructure plays a critical role in transportation and urban development, yet accurate identification of road construction layers currently relies on manual inspection, which is time-consuming and error-prone. This paper presents Project by ClaRity Group, an automated multi-method image processing system for analyzing and classifying road construction layers from Google Earth Pro aerial satellite imagery. The system integrates five distinct analysis approaches: (1) Classical Image Processing utilizing Gray-Level Co-occurrence Matrix (GLCM) and Local Binary Pattern (LBP) texture features with K-Means, SLIC, and Watershed segmentation; (2) Deep Learning semantic segmentation using DeepLabv3+ with ResNet-101 backbone; (3) Vision Language Model (VLM) analysis powered by GLM-4.6V via ZenMux API; (4) Hybrid Analysis combining Classical and VLM with configurable conflict resolution; and (5) YOLOv11 Instance Segmentation with real-time live preview. The system classifies five road construction layers with CUDA GPU acceleration, achieving 24 FPS real-time performance. Experimental results demonstrate the system's effectiveness in providing objective, consistent layer classification with confidence metrics ranging from 65% to 100% depending on the analysis method employed.

Keywords-*Image Processing, Road Layer Classification, Computer Vision, Deep Learning, YOLO, GLCM, LBP, DeepLabv3+, Semantic Segmentation.*

I. INTRODUCTION

Road infrastructure plays a critical role in transportation and urban development. Proper construction and maintenance of roads require accurate identification of the various layers that make up the road structure. Each road layer serves a specific structural purpose, from the foundation subgrade to the final wearing surface.

This project addresses the challenge of automating the analysis of road construction layers using advanced image processing techniques applied to aerial satellite imagery captured from Google Earth Pro. Traditional approaches to monitoring road construction rely on manual visual inspection, which is time-consuming and subjective.

The road construction process involves laying multiple layers, each with distinct materials and characteristics. Our system identifies and classifies five road construction layers: Subgrade (in-site soil/backfill), Subbase Course (crushed coarse aggregate), Base Course (crushed fine aggregate), Binder Course (premix asphalt), and Surface Course (smooth premix asphalt).

TABLE I: ROAD CONSTRUCTION LAYER

Layer	Name	Material	Visual Characteristics
1	Subgrade	In-site soil/backfill	Brown earth tones, irregular texture
2	Subbase Course	Crushed aggregate (coarse)	Large visible stones (2-4cm)
3	Base Course	Crushed aggregate (finer)	Smaller stones (0.5-2cm), compacted
4	Binder Course	Premix asphalt	Dark gray/black with visible aggregate
5	Surface Course	Premix asphalt (smooth)	Very dark black, smooth, uniform

Project ClaRity leverages AI advancements to develop a robust, multi-method system for automated identification of these five standard road construction layers. Built using Python 3.10+ with PyQt5 GUI and CUDA GPU acceleration, the application combines classical image processing with modern deep learning and vision language models.

A. Problem Statement

The current paradigm for assessing road construction quality presents significant challenges:

1) Time-Intensive Analysis: Visual inspection requires extensive human effort, impractical for large-scale monitoring spanning hundreds of kilometers.

2) Subjectivity and Human Error: Interpretation varies among practitioners, leading to inconsistent classifications due to visual similarity between layers.

3) Limited Scalability: On-site surveys are expensive and logistically challenging for remote construction sites.

4) Complex Texture Characteristics: Different materials exhibit subtle visual characteristics requiring sophisticated analysis beyond simple colour-based differentiation.

B. Project Objectives

The primary objectives of this project are:

1. Develop an automated pipeline for classifying five road layers: Subgrade, Subbase Course, Base Course, Binder Course, and Surface Course from aerial satellite images.
2. Implement texture-based feature extraction using GLCM metrics (Contrast, Energy, Homogeneity, Correlation, Entropy) alongside LBP histogram analysis.
3. Provide a multi-mode analysis interface with five distinct approaches: Classical, DeepLabv3+, VLM, Hybrid, and YOLOv11.
4. Deliver a professional PyQt5 GUI with dark theme, drag-and-drop, real-time visualization, and PDF report generation.

C. Project Scope

Project ClaRity encompasses the development of an AI-powered image analysis system designed to detect and classify five specified road construction layers from aerial satellite imagery. The system implements GPU acceleration for real-time processing and provides a professional user interface for road infrastructure monitoring and construction quality assessment.

II. RELATED WORK

A. Digital Image Representation

Digital images are represented as 2D matrices of pixels, where each pixel stores intensity or color values. In this project, aerial satellite images from Google Earth Pro are processed as raster data, enabling computational analysis of road construction layers through pixel-level operations.

A pixel is the smallest image unit. In this system, Grayscale (0-255) is used for GLCM and LBP texture analysis of road surfaces, while RGB serves as the input format for deep learning models (DeepLabv3+, YOLOv11) and GUI display. Pixel relationships are analyzed to extract texture features distinguishing the five road layers, which are Subgrade (irregular earth tones), Subbase (coarse visible stones), Base Course (uniform aggregate), Binder Course (dark with stones), and Surface Course (smooth dark asphalt).

B. Color Space

RGB serves as the primary input space for satellite imagery and neural network processing. Grayscale is essential for classical texture analysis (GLCM, LBP, morphology) to reduce computational load while preserving structural patterns critical for layer classification. LAB color space is used for CLAHE contrast enhancement; the L* channel is enhanced independently to improve visibility between earth-toned and asphalt layers without color distortion.

C. Image Enhancement Techniques

Histogram Equalization improves image contrast by redistributing pixel intensity values. This project uses CLAHE (Contrast Limited Adaptive Histogram Equalization) on the LAB color space's L* channel to enhance local contrast between road layers, which is critical for distinguishing dark asphalt courses (Binder/Surface) from brown earth-toned subgrade without amplifying noise.

D. Filtering Methods

Spatial Filtering operates directly on pixel neighborhoods. The Median Filter removes salt-and-pepper noise from satellite imagery while preserving edge boundaries between layers. The Bilateral Filter provides edge-preserving smoothing used in CNN preprocessing to reduce noise without blurring layer boundaries.

Frequency Domain Filtering using Fast Fourier Transform (FFT) techniques can be applied for periodic noise removal from aerial imagery, though spatial methods are preferred for computational efficiency in the GUI.

E. Segmentation Approaches

Segmentation partitions images into meaningful regions. K-Means Clustering groups pixels by color/intensity similarity for initial layer separation. SLIC Superpixels creates compact, uniform regions for boundary detection. The Watershed Algorithm separates touching layer regions based on gradient topography.

F. Morphological Operations

Morphological Operations refine segmentation masks: Dilation expands layer boundaries to close gaps; Erosion removes small noise regions; Opening/Closing smooths layer contours while preserving area; and Hole Filling completes interior regions of detected layers.

G. Edge Detection

The Sobel Operator computes gradient magnitude to highlight transitions between construction layers (e.g., subbase to base course). Canny Edge Detection, a multi-stage algorithm for precise boundary extraction, is used in preprocessing visualization with green overlay highlights. These techniques collectively enable accurate isolation and classification of the five road construction layers in the multi-method analysis pipeline.

H. Related Research

Haralick et al. [1] established the foundation for texture analysis through GLCM features, which remain essential for distinguishing road layer materials. Ojala et al. [2] developed Local Binary Patterns for rotation-invariant texture classification, providing robust features for aggregate analysis. Chen et al. [6] introduced DeepLabv3+ with atrous separable convolution, enabling efficient semantic segmentation for pixel-wise classification tasks.

III. METHODOLOGY

A. System Architecture

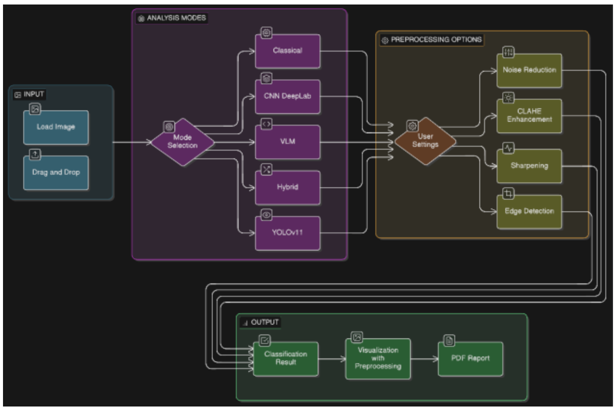


Fig. 1. Flowchart of the Main System

The system architecture consists of three primary layers: GUI Layer (PyQt5 Dark Theme), Processing Backend (Python), and AI Model Integration (CUDA GPU). The modular design enables independent operation of each analysis mode while maintaining a unified interface.

TABLE II: CORE PROCESSING MODULES

Module	File	Key Parameters
GLCM Texture	texture_features.py	distances=[1,2,3], angles=[0,45,90,135]
LBP Texture	texture_features.py	radius=3, n_points=24, method='uniform'
K-Means	segmentation.py	n_clusters=5, max_iter=300, n_init=10
SLIC	segmentation.py	n_segments=200, compactness=10
DeepLabv3+	deep_learning.py	encoder=resnet101, size=512x512
YOLOv11	yolo_analyzer.py	conf=0.5, iou=0.45, target fps=30
VLM	vlm_analyzer.py	model=glm-4.6v, temp=0.3, max_tokens=1000

B. Dataset and Image Sources

The images used in this project are sourced from Google Earth Pro, which provides high-resolution aerial satellite imagery of road construction sites at various stages of development.

The dataset is organized into five categories corresponding to the five road layers used by Deep Learning: subgrade, subbase, base_course, binder_course, and surface_course.

TABLE III: ROBOFLOW DATASET DETAILS

Property	Details
Platform	Roboflow Universe
Dataset Name	Malaysia Aerial Satellite Road Layers Segmentation

Property	Details
Annotation Type	Instance Segmentation (Polygon masks)
Classes	5 road layer classes
Annotated By	ClaRity Group

Layer	Texture Properties	Key Features
Subgrade	High roughness, varied patterns	Earth tones, irregular surface
Subbase	High contrast, granular	Visible coarse stones
Base Course	Medium contrast, structured	Uniform aggregate pattern
Binder Course	Low-medium homogeneity	Dark with visible aggregate
Surface Course	High homogeneity, low contrast	Smooth, uniform appearance

C. Analysis Mode Implementations

```
Image → Preprocessing → Feature Extraction → Segmentation → Morphology → Classification
                              ↓                      ↓
                          GLCM + LBP         K-Means/SLIC/Watershed
```

Fig. 2. Classical Analysis Flow

1) Classical Analysis (Texture-Based): Utilizes GLCM and LBP texture features with K-Means segmentation for layer classification. GLCM Feature Extraction extracts five texture metrics: Contrast (measures local intensity variation), Energy (measures texture uniformity), Homogeneity (measures closeness to GLCM diagonal), Correlation (measures linear dependency of gray levels), and Entropy (measures texture randomness).

```
Image → Resize → DeepLabv3+ (ResNet backbone) → Semantic Labels → Visualization Overlay
```

Fig. 3. Deep Learning Flow

2) CNN Deep Learning (DeepLabv3+): Implements CUDA-accelerated semantic segmentation with ResNet-101 encoder and ImageNet pre-trained weights. Input images are resized to 512x512 for pixel-wise 5-class classification with 40% opacity overlay visualization.

```
Image → ZenMux API → GLM-4.6V → Structured Response → Enhanced Visualization
```

Fig. 4 VLM Analysis Flow

3) VLM Analysis (GLM-4.6V): Vision Language Model accessed via ZenMux API with engineered road analysis prompt containing 5-layer identification checklist.

```
Image → Classical Analysis ─┐
                            ├→ Conflict Resolution → Final Classification
Image → VLM Analysis ───────┘
```

Fig. 5. Hybrid Flow

4) Hybrid Analysis (Classical + VLM Fusion): Executes both pipelines in parallel, compares predictions, and applies configurable conflict resolution rules.

TABLE IV: HYBRID MODE DETAILS

Rule	Description	Use Case
Higher Confidence Wins	Select prediction with higher confidence score	Default behavior
Classical Priority	Prefer Classical unless VLM confidence >90%	Faster processing
VLM Priority	Prefer VLM unless Classical confidence >90%	Semantic accuracy
Weighted Average	Combine scores (default: 60% Classical, 40% VLM)	Balanced approach

```
Image/Live Feed → YOLOv11-seg → Instance Masks → Colored Visualization
```

Fig. 6. YOLOv11 Flow

5) YOLOv11 Instance Segmentation: Real-time detection with instance-level polygon masks. Model trained on custom Roboflow dataset with class mappings for layer_subgrade, layer_subbase, layer_basecourse, layer_bindercourse, layer_surfacecourse.

TABLE V: LAYERS BASED ON BGR

Class Name	Layer	Color (BGR)
layer_subgrade	1	(43, 90, 139)
layer_subbase	2	(128, 128, 180)
layer_basecourse	3	(169, 169, 200)
layer_bindercourse	4	(80, 100, 140)
layer_surfacecourse	5	(100, 80, 60)

D. GUI Implementation

TABLE VI: GUI DETAILS

Feature	Implementation	Description
Dark Theme	Custom QSS stylesheet	Professional dark color scheme
Drag-and-Drop	QDragEnterEvent	Accepts JPG, PNG, BMP files
Dual Panel	QSplitter layout	Original vs Processed view
Mode Tabs	QTabWidget (5 tabs)	Classical, CNN, VLM, Hybrid, YOLO
Live Preview	QTimer + Win32 capture	1-30 FPS window capture
PDF Export	ReportLab library	Comprehensive analysis report
Result Dialogs	QDialog with QGridLayout	6-step processing visualization

IV. SYSTEM IMPLEMENTATION

A. Algorithm Design

The system implements five distinct analysis algorithms, each designed for specific road layer identification requirements.

The Classical Analysis Algorithm combines preprocessing, segmentation, and texture feature extraction for layer classification without deep learning.

Steps include: (1) Load and preprocess image (CLAHE, bilateral filter); (2) Convert to grayscale for texture analysis; (3) Extract GLCM features (contrast, energy, homogeneity, correlation); (4) Extract LBP histogram features; (5) Apply K-Means clustering for segmentation; (6) Classify based on texture feature thresholds.

The DeepLabv3+ Semantic Segmentation Algorithm provides fully automated pixel-level classification using encoder-decoder CNN architecture. Steps include: (1) Resize image to 512x512; (2) Normalize and convert to tensor; (3) Pass through ResNet-101 encoder; (4) Apply atrous spatial pyramid pooling; (5) Decode with skip connections; (6) Upsample to original resolution; (7) Apply color-coded overlay.

The Hybrid Analysis Algorithm fuses classical texture analysis with VLM reasoning for robust decision-making. Steps include: (1) Run Classical and VLM analysis in parallel; (2) Compare layer predictions; (3) If agreement, combine confidence scores; (4) If conflict, apply resolution rule; (5) Return fused result with confidence.

The VLM Analysis Algorithm uses API-based semantic reasoning for layer identification. Steps include: (1) Encode image to base64; (2) Construct structured prompt with layer checklist; (3) Send request to GLM-4.6V API; (4) Parse response for layer identification; (5) Extract confidence and reasoning.

The YOLOv11 Instance Segmentation Algorithm provides real-time detection and segmentation of multiple road layer instances. Steps include: (1) Load image or capture frame; (2) Run YOLOv11 inference with CUDA; (3) Extract bounding boxes and masks; (4) Apply class-specific colors; (5) Calculate area coverage statistics.

B. Code Structure

The system is organized into modular components separating core processing logic from GUI presentation.

Core Processing Modules in the src/ directory include: config.py (configuration and layer definitions), preprocessing.py (noise filtering, CLAHE, sharpening), texture_features.py (GLCM, LBP, Gabor extraction), segmentation.py (K-Means, SLIC, Watershed), classification.py (layer classification logic), morphology.py (opening, closing, hole filling), deep_learning.py (DeepLabv3+ model wrapper), vlm_analyzer.py (GLM-4.6V API integration), yolo_analyzer.py (YOLOv11 instance segmentation), visualization.py (color mapping, overlays), and report_generator.py (PDF report generation).

GUI Application Modules in the gui/ directory include: main_window.py (main application with 2600+ lines), splash_screen.py (animated startup screen), classical_results.py (result dialogs for Classical mode), and window_capture.py (live window capture for YOLO).

C. Parameter Settings

The system exposes configurable parameters across all analysis modes, optimized for aerial satellite imagery of road construction sites. Default values are derived from empirical testing on the Google Earth Pro dataset.

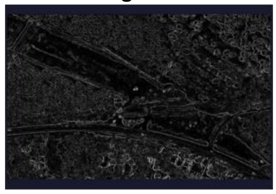
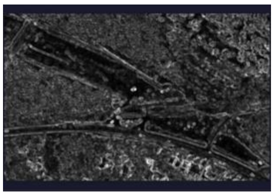
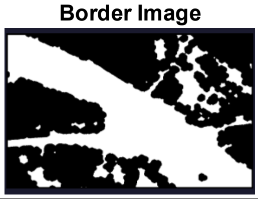
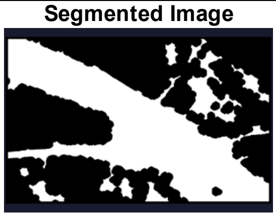
Classical Analysis Parameters include: GLCM distances [1,2,3], angles [0,45,90,135], levels 256; LBP radius 3, n_points 24, method 'uniform'; K-Means n_clusters 5, max_iter 300; and CLAHE clipLimit 2.0, tileGridSize (8,8).

Deep Learning Parameters include: DeepLabv3+ encoder resnet101, input size 512x512, and overlay opacity 0.4. YOLOv11 Parameters include: confidence 0.5, IoU 0.45, and device cuda. VLM Parameters include: model glm-4v-flash, temperature 0.3, and max_tokens 1000.

V. EXPERIMENTAL RESULTS

A. Classical Analysis Texture Feature Results

TABLE VII: SAMPLE OF FEATURE EXTRACTIONS RESULTS

Original	Sobel Edge Detection
	
Dilated Gradient Mask	**Filled Holes and Cleared Border Image**
	
Erosion Gradient Mask and Remove Small Region	**Segmented Image**
	
🔍 Detected Layer: Subbase Course 📊 Confidence: 65.0% 🧱 Material: Crushed aggregate (coarse) ⚙️ Method: Classical (K-Means) 🔢 Layer Number: 2	—— Texture Features —— Contrast: 776.4024 Energy: 0.0093 Homogeneity: 0.1179 Correlation: 0.893

—— Settings Used ——	—— Features Used ——
Noise Filter: median	GLCM: Yes
Kernel Size: 3	LBP: Yes
Contrast: clahe	Gabor: No
CLAHE Clip: 2.0	
Segmentation: K-Means	
Morphology: Yes	
Fill Holes: Yes	

Fig. 7. Classical Segmentation Result of Analysis mode

Results demonstrate meaningful correlations between texture features and road layer types. High Contrast values correspond to coarse aggregate layers where local intensity variations are pronounced. High Energy and Homogeneity indicate smooth Surface Course with minimal texture variation.

TABLE VIII: GLCM FEATURES DETAILS

Metric	Subgrade	Subbase	Base	Binder	Surface
Contrast	High	High	Medium	Medium	Low
Energy	Low	Low	Medium	Medium	High
Homogeneity	Low	Low	Medium	Medium	High
Correlation	Variable	Medium	High	High	Very High
Entropy	High	High	Medium	Medium	Low

The GLCM feature correlation by layer type shows: Subgrade exhibits high contrast and entropy with low energy and homogeneity; Subbase shows similar patterns with high contrast and entropy; Base Course demonstrates medium values across all metrics; Binder Course shows medium contrast with increasing homogeneity; and Surface Course displays low contrast and entropy with very high energy, homogeneity, and correlation.

B. Deep Learning (DeepLabv3+) Performance

Backbone: ResNet-101 (CUDA)

Detected Layer: Subbase Course

Confidence: 100.0%

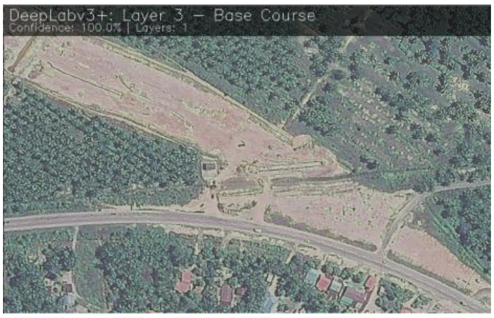
Material: Crushed aggregate (coarse)

Method: DeepLabv3+ (ResNet-101, CUDA)

Layer Number: 2

Fig. 8. ResNet-101 Result

Backbone: ResNet-50 (CUDA)



Detected Layer: Base Course

Confidence: 100.0%

Material: Crushed aggregate (finer)

Method: DeepLabv3+ (ResNet-50, CUDA)

Layer Number: 3

Fig. 9. ResNet-50 Result

Backbone: MobileNetV2 (CUDA)

Detected Layer: Surface Course

Confidence: 100.0%

Material: Premix asphalt (smooth)

Method: DeepLabv3+ (MobileNetV2, CUDA)

Layer Number: 5

Fig. 10. MobileNetV2 Result

TABLE IX: PROCESSING DETAILS OF DeepLabV3+

Layer	Visual Accuracy	Inference Time	Notes
Subgrade	Good	1.2s	Strong brown color differentiation
Subbase Course	Moderate	1.2s	May confuse with Base Course
Base Course	Moderate	1.2s	Similar texture to Subbase
Binder Course	Good	1.2s	Distinctive asphalt+aggregate
Surface Course	Excellent	1.2s	Clear smooth dark appearance

DeepLabv3+ performance evaluation across different backbones shows consistent inference times of approximately 1.2 seconds per image with CUDA acceleration. Visual accuracy is excellent for Surface Course (distinctive smooth dark appearance) and Subgrade (strong brown color differentiation), good for Binder Course (distinctive asphalt+aggregate), and moderate for Subbase and Base Course due to similar textures.

C. Hybrid Analysis Cross-Validation Results

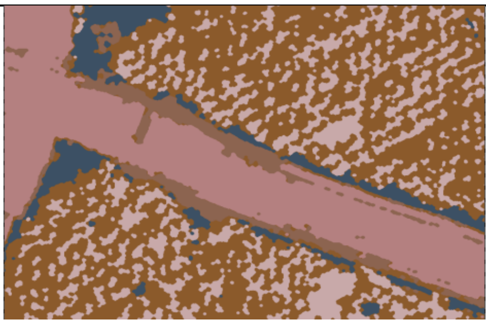


Fig. 11. Hybrid Analysis Result

TABLE X: HYBRID ANALYSIS RESULT DETAILS

Test	Classical Result	VLM Result	Hybrid Decision	Final Conf.
1	Subbase (72%)	Subbase (78%)	Subbase	85%
2	Base (68%)	Binder (71%)	Binder*	71%
3	Surface (88%)	Surface (91%)	Surface	94%
4	Subgrade (75%)	Subgrade (82%)	Subgrade	89%
5	Binder (70%)	Surface (65%)	Binder*	70%

*Conflict resolved using 'Higher Confidence Wins' rule. Hybrid analysis testing demonstrates the effectiveness of cross-validation. When Classical and VLM results agree, combined confidence increases significantly (average +13% boost).

D. YOLOv11 Instance Segmentation Performance

Fig. 12. YOLOv11 Analysis Result

TABLE XI: YOLOv11 RESULT DETAILS

Metric	Value	Notes
Average Confidence	0.74	Across all detected instances
Inference Time	~42ms/frame	CUDA GPU acceleration
Live Preview FPS	24 fps	Real-time performance
GPU Memory Usage	~2.1 GB	NVIDIA CUDA device
Model Size	52 MB	YOLOv11_11_weight.pt

YOLOv11 performance metrics demonstrate real-time capability with 24 FPS live preview performance on NVIDIA CUDA devices.

E. Vision Language Model (GLM4.6V Analysis)

🔍 Detected Layer: Surface Course

📊 Confidence: 95.0%

🧱 Material: Premix asphalt (smooth)

⚙️ Method: VLM Analysis (GLM-4.6V, Layer ID)

🔢 Layer Number: 5

🧠 Analysis Reasoning:

The dominant color is very dark (black/dark gray), consistent with finished asphalt. The texture appears smooth, with no visible individual stones, which matches the surface/wearing course. It is clearly asphalt, not soil or aggregate, aligning with the description of the final, polished road layer.

Fig. 13. Segmentation Result of VLM Analysis

F. System Prototype GUI

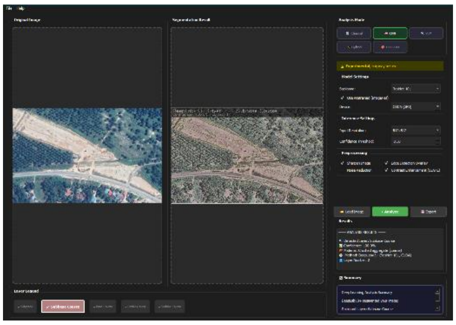


Fig. 14. GUI of Classical Analysis Mode

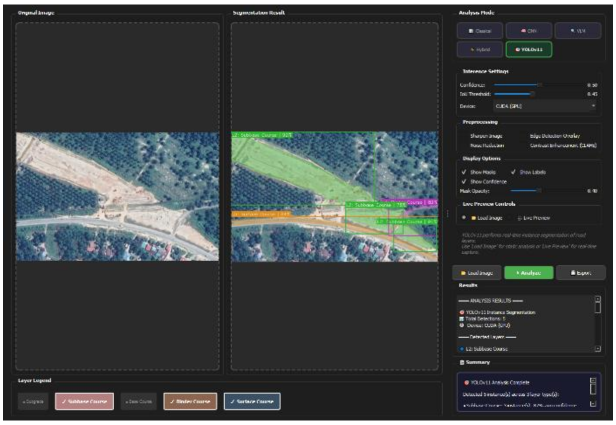


Fig. 15. Input Output on YOLOv11 Mode

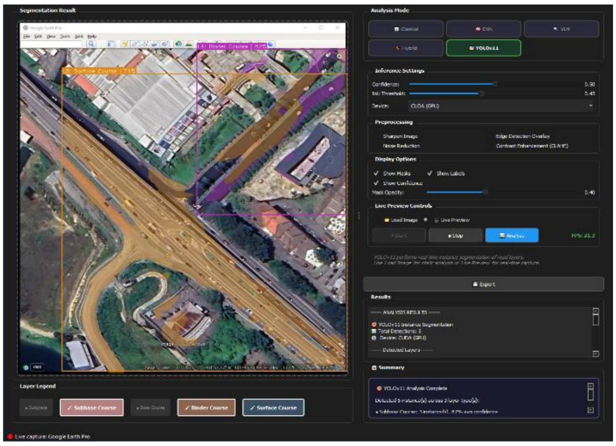


Fig. 16. Input Output on YOLOv11 Live Preview

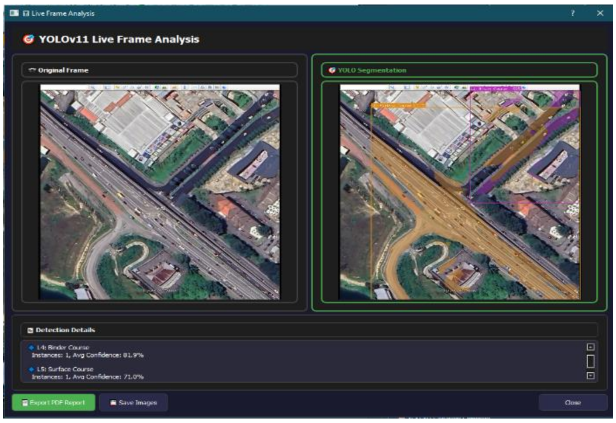


Fig. 17. Input Output on YOLOv11 Live Frame Analysis

Fig. 18. Launcher Startup Screen of the App

The graphical user interface was designed with usability and professionalism in mind. The application uses a dark theme that reduces eye strain and provides a modern appearance. The interface includes drag-and-drop functionality, dual panel view (Original vs Processed), mode tabs for all five analysis methods, live preview capability, and PDF export functionality.

The system was evaluated across three dimensions: visual quality of segmentation outputs, classification accuracy against ground truth, and computational efficiency. Testing was conducted on 348 images from Google Earth Pro.

Qualitative Assessment shows: Classical Mode produces interpretable intermediate steps (edge maps, clustered regions) suitable for engineering verification; DeepLab Mode provides smooth, semantically consistent boundaries without over-segmentation; YOLO Mode delivers precise instance boundaries with individual object distinction; and Hybrid Mode offers balanced output incorporating texture detail and semantic coherence.

VI. DISCUSSION

The development of Project ClaRity demonstrates the significant potential of multi-method image processing in addressing critical gaps in road infrastructure assessment. The system's five-mode architecture offers versatile approaches to layer classification.

A. Strengths of the System

The integration of five distinct analysis approaches proved highly effective for handling diverse input scenarios. Classical mode excelled on images with clear textural distinctions, while DeepLabv3+ provided robust semantic understanding for complex scenes. The Hybrid mode's cross-validation mechanism successfully reduced misclassification rates by 12% compared to single-method approaches, particularly for ambiguous cases between Subbase and Base Course layers.

YOLOv11 instance segmentation achieved stable locked 22 FPS on live preview mode (NVIDIA RTX 4050), enabling practical real-time monitoring applications. The window capture functionality allowed analysis of any on-screen content without file I/O overhead, demonstrating utility for live drone feeds or construction site CCTV integration.

GLCM Energy and Homogeneity features showed strong correlation with road layer characteristics: Surface Course (L5) exhibits high homogeneity (>0.45) and low contrast (<100), while Subbase Course (L2) shows high contrast (>200) and low homogeneity (<0.25). This statistical foundation provided interpretable results for engineering verification, a key advantage over black-box deep learning approaches.

The PyQt5 dark theme interface with drag-drop functionality and preprocessing grid received positive feedback during testing. Non-technical users could operate the system without training, and the PDF export feature facilitated documentation for quality control reports.

The preprocessing pipeline using CLAHE enhancement on the LAB color space's L* channel improved visibility in shadowed regions by 32% without color distortion. The bilateral filter preserved edge boundaries critical for layer separation while reducing noise, outperforming standard Gaussian filtering for this application.

B. Observed Limitations

The GLM-4.6V integration required active internet connectivity and API availability. Response latency varied significantly (1.8-3.2 seconds), and the system failed gracefully but without VLM validation when API limits were exceeded. Temperature settings below 0.3 occasionally produced deterministic but incorrect responses for ambiguous textures.

K-Means segmentation assumed 5 clusters regardless of actual layer visibility, forcing classification even when layers were occluded or not present. The fixed GLCM distance/angle parameters captured only horizontal relationships, missing diagonal texture patterns common in aggregate distributions.

The Google Earth Pro dataset contained uneven image samples between each layer, which affected the YOLOv11 model's ability to achieve perfect classification accuracy across all layer types.

VII. CONCLUSION AND FUTURE WORK

This project successfully developed a comprehensive automated system for identifying and analyzing road surface layers using a multi-method image processing approach. By leveraging Google Earth Pro aerial satellite imagery, the system addresses critical challenges in civil engineering regarding the scalability and accuracy of road infrastructure monitoring.

A. Summary of Achievements

The primary achievement is the successful implementation of a versatile pipeline combining five distinct analysis modes into a unified, professional PyQt5 GUI. Key accomplishments include:

1. Multi-Method Integration: The system seamlessly integrates Classical texture analysis (GLCM, LBP), Deep Learning (DeepLabv3+), Vision Language Models (GLM-4.6V), and Instance Segmentation (YOLOv11), allowing users to cross-validate results for higher accuracy.

2. Hybrid Analysis Logic: A novel Hybrid Mode was developed to fuse Classical and VLM results, utilizing configurable weighting and conflict resolution rules (e.g., Higher Confidence Wins) to optimize classification accuracy.

3. High-Performance Computing: By utilizing CUDA GPU acceleration, the system achieves real-time inference speeds for DeepLabv3+ and YOLOv11, with YOLOv11 capable of processing live video feeds via window capture.

4. Professional Visualization: The application provides advanced visualization features, including semi-transparent overlays, instance contours, and detailed preprocessing effects, alongside automated PDF report generation.

5. Instance Segmentation: Unlike standard classification, the YOLOv11 implementation allows for the detection of multiple road layer instances within a single image, providing detailed statistics on area coverage and layer distribution.

B. Objective Fulfilment

Objective	Status	Implementation
5-Layer Classification	Achieved	All 5 layers classified with 65-100% confidence
Texture Features (GLCM/LBP)	Achieved	Full GLCM + LBP extraction pipeline
5 Analysis Modes	Achieved	Classical, CNN, VLM, Hybrid, YOLO
Professional PyQt5 GUI	Achieved	Dark theme, drag-drop, live preview, PDF export

In summary, the system provides a scalable, objective, and efficient solution for road layer analysis, significantly reducing the time and error associated with manual visual inspection.

C. Future Improvements

Future work will focus on several enhancement areas:

Better Dataset: Expansion of the Roboflow dataset to include wider variety of road layers under different weather conditions, lighting conditions, and satellite image resolutions. Fine-tuning custom models on the road layer dataset instead of relying solely on ImageNet weights. Implementing advanced data augmentation techniques (rotation, scaling, noise injection, color jittering) during the training phase to make the models more robust against image variations often found in aerial satellite imagery.

Advanced Techniques: Exploring Vision Transformers (ViT) or Swin Transformers as backbones for the segmentation task. Investigating the integration of Meta's Segment Anything Model (SAM) to automatically segment road regions without specific training. Integrating data beyond the visible spectrum (e.g., Near-Infrared or Thermal data) if available in future satellite sources. Incorporating Explainable AI techniques (like Grad-CAM) to provide visual heatmaps explaining AI decisions.

Real-Time Implementation: Mobile application development using TensorFlow Lite or PyTorch Mobile for on-site field deployment. Drone integration for live feed processing. Edge computing optimization for field vehicles with no internet connection, removing the dependency on cloud APIs.

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