# Smarter Mining: Detecting Coal Trucks with Real-Time AI

*Revolutionizing mining operations with custom object-detection model*

By Team **QuantumSenses**

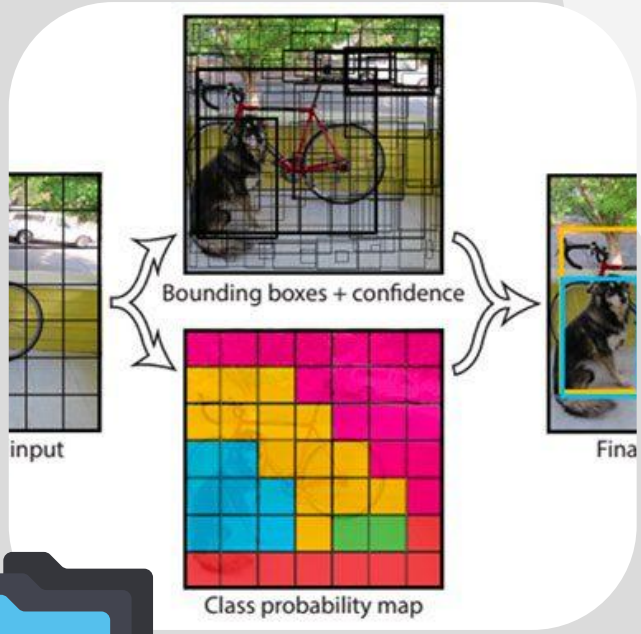
# Untracked Trucks, Missed Opportunities

Mining companies face **chaos in coal logistics**:

- Trucks carrying coal deposits aren't **systematically tracked**.
- Delays and bottlenecks disrupt operations.
- **Untracked movements** increase the risk of theft and mismanagement.

This inefficiency translates to **lost revenue, increased costs,** and **environmental impact**.

**"It's time for mining logistics to enter the era of automation"**




# The Solution: *Real-Time Object Detection at Work*

Introducing an AI-powered object detection system to automate truck monitoring.
Built on **YOLOv3**, a cutting-edge algorithm for:

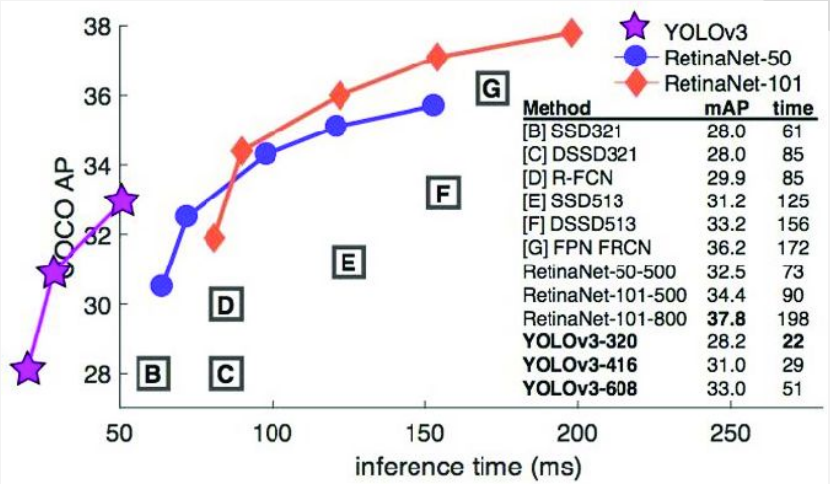
- Real-time detection of **trucks with coal deposits**.
- Precision, even in challenging environments like dust and poor lighting.

**Deployed on edge devices** for instant insights right on the ground.

**“From chaos to clarity, our model in action”**

# Why YOLOv3?

- **Real-Time Ready:** Inference so fast, decisions happen in the blink of an eye.
- **Built for the Tough Stuff:** Detects small objects (like coal piles) in complex scenes.
- **Deploy Anywhere:** Compact enough to run on edge devices—right where you need it.
- **Better Than the Rest:**
    - Faster than Faster R-CNN
    - Smarter than SSD
    - Robust enough for real-world mining operations



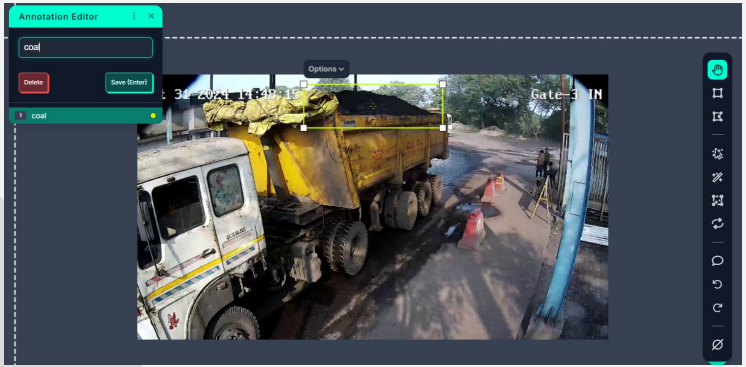

| Method | mAP | time |
|---|---|---|
| [B] SSD321 | 28.0 | 61 |
| [C] DSSD321 | 28.0 | 85 |
| [D] R-FCN | 29.9 | 85 |
| [E] SSD513 | 31.2 | 125 |
| [F] DSSD513 | 33.2 | 156 |
| [G] FPN FRCN | 36.2 | 172 |
| RetinaNet-50-500 | 32.5 | 73 |
| RetinaNet-101-500 | 34.4 | 90 |
| RetinaNet-101-800 | **37.8** | 198 |
| **YOLOv3-320** | 28.2 | **22** |
| **YOLOv3-416** | 31.0 | 29 |
| **YOLOv3-608** | 33.0 | 51 |

# How It Works

## Custom Dataset

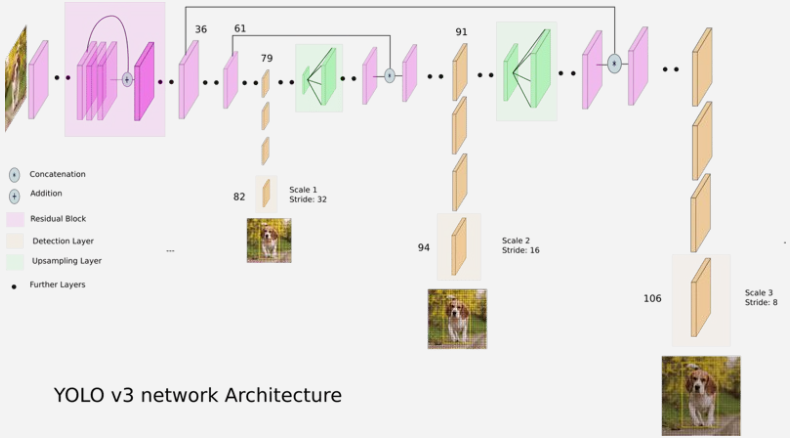
Captured images from the mining grounds using **high-resolution cameras** at various times of the day to account for **different lighting conditions**. Diverse scenarios included:

- Trucks partially loaded with coal.
- Varying backgrounds (e.g., piles of coal, mining machinery, dirt roads).



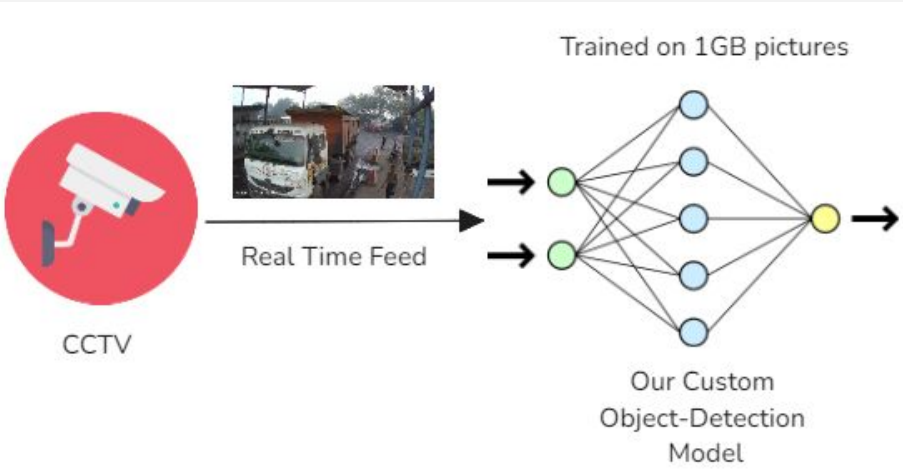

## Training the Model

- A **single-shot detector** that processes the entire image in one forward pass.
- **Darknet-53** Backbone: A convolutional neural network optimized for feature extraction.
- **Multi-Scale Detection**: YOLOv3 uses three scales to detect objects of varying sizes.




YOLO v3 network Architecture

# Process Workflow



# The Impact

## Smarter Scheduling

Automates truck tracking, eliminating bottlenecks.

## Lower Costs

Reduces human intervention and streamlines operations.

## Enhanced Security

Tracks every truck to prevent unauthorized movement.

## Actionable Insights

Real-time analytics for data-driven decisions in fleet and resource management.

## Environmental Win

Optimized routes and reduced idle times cut down emissions.

**“Efficiency, Security, and Data like never before”**

# Scalability and Future

## Expansion across multiple mining sites

**NVIDIA Jetson** or cloud-edge hybrid systems enable rapid deployment without extensive infra changes.

## Load Balancing and Distributive Processing

**Distributed inference pipelines** where edge devices process initial frames and relay results to centralized servers for analysis.

## Adopting Advanced Models

Transition to newer versions of YOLO (like **YOLOv5 or YOLOv8**) or explore transformer-based architectures such as **DETR**

## Global Deployment and Customization

Extend the model to handle datasets from **different geographies** and types of mining (e.g., **iron ore, copper, or gold**).

# The Team 😎

**We are a team of 2 passionate student devs aiming to solve real problems in mining automation.**

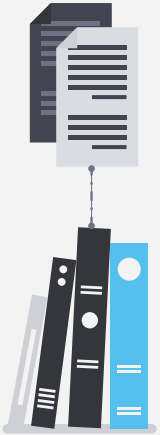
## Aditya Subramanian

AI/ML Research, Deep Learning Architect

## Aditya Sinha

MLOps Engineer, Data Strategist

# References

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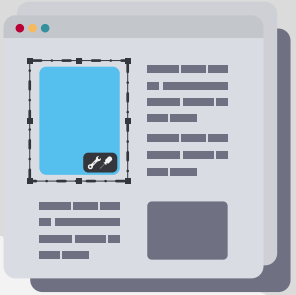

# Thank You!