Big Data Analysis on Road Attributes

IMPERIAL THE WORLD BANK

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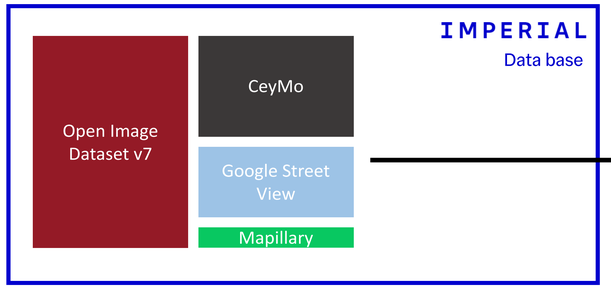
Internalising Road Safety in Project Funding

The Environmental and Social Framework of the World Bank requires that all financed projects proactively **avoid or mitigate potential road safety risks and their impacts**, to address traffic and road safety issues in low- and medium-income countries (LMICs).

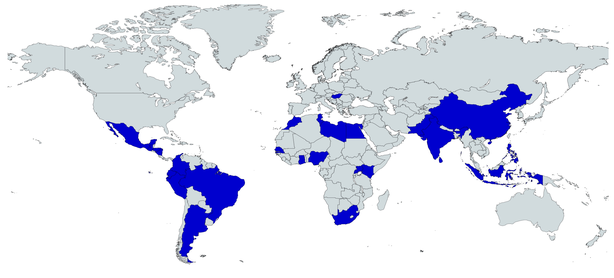
To evaluate the road safety performance based on existing conditions, the World Bank developed the **Road Safety Screening and Appraisal Tool** (RSSAT). These evaluations are time-consuming and costly, hence there is a need for **automation in detecting road features** from videos and photos, particularly within the context of LMICs.

Multi-Layer Model

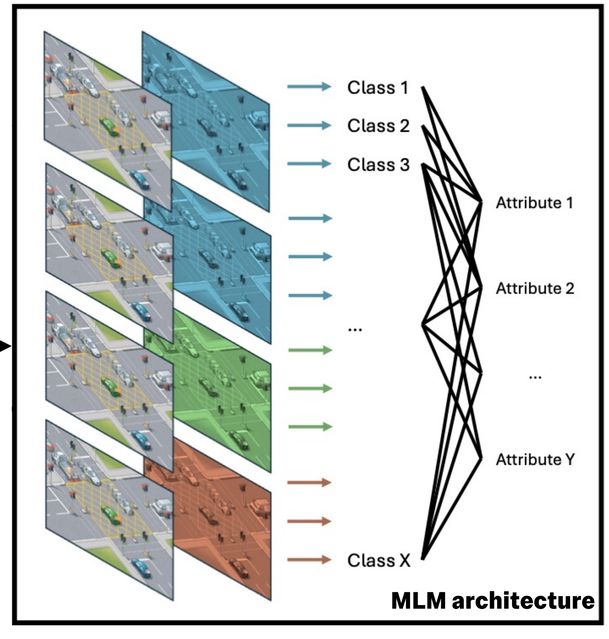
The Multi-Layer Model (MLM) aggregates ground level (model 1 & 2), aerial view (model 3), and lane & road marking (model 4) YOLOv8 models. It can detect 11 attributes of road safety: **Segment characteristics**, **Dominant roadside object**, **Intersection characteristics**, and **Pedestrian crossings**.



+30,000 images gathered from Open Image Dataset v7, CeyMo[1], Google Street View, and Mapillary over twenty-three LMIC.



Requirement categories	Attributes	Output
Segment Characteristics	Median type	• Central line • Central hatching • Physical median • Safety barrier
	Road marking & Road sign	• Poor • Fair • Good
	Pedestrian facilities	• None • Sidewalk • Protected sidewalk
	Bicycle facilities	• No • Bike lane • Protected bike lane
Intersection Characteristics	Grade sperated junctions	• None • Present
	Roundabouts	• None • Present
	Signalised junctions	• None • Present
Dominant Roadside objects	Safety barrier	• None • Present
	Static roadside object	• None • Present
Pedestrian Crossing	Marked crossing	• None • Present
	Signalised crossing	• None • Present



Comparison between input picture and detection of classes for the 3rd model in Layer 2 of the MLM

Comparison between input picture and detection of classes for the 2nd model in Layer 1 of the MLM

Results of Multi-Layer Model

The **key metrics** (**sensitivity**, **specificity**, **precision**, and number of **occurrences**) are shown for each model and for every class in the table *infra.*

	Classes	Sensitivity	Specificity	Precision	Occurrences
Layer 1 Model 1	Car	0.691	0.918	0.724	1,444
	Traffic light	0.533	0.960	0.727	1,007
	Traffic sign	0.634	0.962	0.612	529
	Tree	0.413	0.870	0.571	1,799
Layer 1 Model 2	Bike lane	0.703	0.987	0.667	74
	Central hatch	0.560	0.996	0.636	25
	Pedestrian Crossing	0.680	0.968	0.576	122
	Physical median	0.617	0.943	0.559	214
	Pole	0.388	0.8941	0.591	580
	Protected bike lane	0.000	0.998	0.000	2
	Protected sidewalk	0.419	0.986	0.317	31
	Safety barrier	0.597	0.965	0.665	216
	Sidewalk	0.472	0.940	0.621	354
Layer 2 Model 3	Grade junction	0.527	0.875	0.611	110
	Roundabout	0.767	0.674	0.682	193
Layer 3 Model 4	Arrow left	0.833	0.999	0.833	18
	Arrow right	0.946	0.997	0.881	55
	Arrow straight	0.960	0.991	0.928	228
	Arrow straight & left	0.956	0.997	0.880	46
	Arrow straight & right	0.923	1.000	1.000	13
	Bike lane	1.000	1.000	1.000	11
	Bus lane	1.000	0.998	0.889	32
	Pedestrian Crossing	0.917	0.998	0.968	132
	Diamond	0.982	0.999	0.982	109
	Line type 1	0.818	0.825	0.851	1,212
	Line type 2	0.712	0.983	0.546	59
	Slow sign	1.000	1.000	1.000	21
	Yellow mark	0.966	0.999	0.933	29

Novelty of the Research

Even though the leader of road object detection, **Mapillary**, already detects 65 road classes, **it fails to detect:** (1) median type such as: central hatching and safety barriers; (2) pedestrian facilities: the difference between a sidewalk and a protected sidewalk; (3) road intersections: neither roundabouts or grade junctions; **while the developed MLM has this capability.**

Moreover, this study focuses on **datasets from LMICs**, while other researches or databases focus only on developed regions and countries.

Limitations of the Project

Despite efforts to collect versatile data, some limitations remain when building the **database**:

- Inconsistency in the quality of pictures
- Lack of diversity in weather and light conditions meaning less unified algorithm
- Lack of method to differentiate between urban and rural areas when collecting data
- Some classes of attributes remain challenging to find adequate amounts of images in order to train the model (such as protected bike lane).

Recommendations for Future Work

- **To gather more data:** strengthen cooperation with local authorities in order to facilitate the use of high precision equipment to update database
- **To ensure annotation quality:** use semi-automated or crowdsourced methods to gain a uniform and comprehensive training dataset
- **To improve model robustness:** expand the dataset to include more challenging scenarios, and deploy techniques such as data augmentation, transfer learning, and domain adaptation
- **To integrate a Digital Twin generator:** track and extract every unique object GPS coordinate via Depth estimation methods.

Acknowledgments

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References

[1] Liu, X., Deng, Z., Lu, H., and Cao, L., 2017. Benchmark for road marking detection: Dataset specification and performance baseline. In: 2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC), pp. 1–6. IEEE.