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Intelligent Anomaly Detection for Lane Rendering Using Transformer with Self-Supervised Pre-Training and Customized Fine-Juning

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Background

- The burgeoning navigation services using digital maps provide great convenience to drivers.
- There are anomalies (errors and/or defects), e.g., irregular shapes, and missing edges or corners, in lane-level rendered map images.
- These anomalies will be equivocal for human drivers' understanding and decision-making during their driving routing which might result in critical unsafe situations.

Aim

- To accurately and effectively detect lane rendering image anomalies;
- To transform the lane rendering anomaly detection problem into a muti-class

I. Image Pre-processing



II. Self-supervised Pre-training



classification problem and leveraging state-of-the-art AI models;

To delivery excellent detection performance in regarding various metrics.

The framework of the proposed pipeline

- > Image pre-processing, which normalizes the inconsistent images into uniform size and format;
- > Self-supervised pre-training, which is tackled by the masked image modeling (MiM) method.
- Customized fine-tuning;
- Post-processing;
- > Tested models:
 - Swin-Transformer (Swin-Trans) ViT
 - Swin-Transformer-UniformMasking (Swin-Trans-UM) BEiT

Evaluation Metrics

Accuracy	Precision	True Positive Rate		
F1-Meassure	> Recall	🕒 Ealco Nogativo Date		

Mask (50% (256×256) Preprocessin (256×256) **Customized Uniform Image Masked Image Frame Pre-trained** Model **IV. Post-processing III. Fine-tuning Classification** Transfer Weights To_Prob **Fine-tuning output** softmax(·) **Prob** = 1 - prob(class0)Swin-Vision Clipping processing Transformer Transformer **Prob** > 0.97? **Prob** < 0.03? Ν **Cross Entropy Fine-tuning Loss** Prob=0 Prob=Prob Prob=1 **Out_Prob Prob** < threshold ' (256×256) **Out_Class: Out Class: <u>Fine-tuning</u>** Input Image Abnormal Normal

Figure 1. The architecture of the proposed four-phase pipeline.

Results

False Negative Rate



Converted the problem of lane rendering image anomaly detection into a classification problem;

Various SOTA computer vision techniques and models were adopted and compared.

Table 1 The model performance regarding different metrics.

Model	Acc	AUC	Precision	Recall	F1-	Param	Epoch	Fine-tuning
					measure		time	Epoch
ViT	0.9489	0.9080	0.9393	0.6178	0.7454	632.20	4210	40
BEiT	0.9413	0.9481	0.7913	0.6996	0.7427	311.53	159	15
Swin-Trans	0.9401	0.9498	0.8518	0.6121	0.7123	86.90	120	280
Swin- Trans-UM	0.9477	0.9743	0.7743	0.8022	0.7805	194.95	223	41

Table 2 The performance of the Swin-Trans-UM_2 and Swin-Trans-UM_9.

Model	Accuracy	AUC	Precision	Recall	F1-measure	

Swin-Trans-UM_2	0.9482	0.9756	0.7813	0.7947	0.7879
Swin-Trans-UM_9	0.9392	0.9731	0.6990	0.8745	0.7770
Swin-Trans-UM_8	0.9477	0.9743	0.7743	0.8022	0.7805



Figure 3. The confusion matrix of Swin-Trans-UM when treated as a 2-class classification and a 9-class multi-label classification.

Conclusions

- > The proposed four-phase pipeline can tackle the lane rendering image anomaly detection task with super performances at high accuracy.
- > The self-supervised pre-training with MiM can greatly improve the model accuracy.
- > The proposed method can improve the efficiency of lane rendering image data anomaly detection reducing labor costs while keeping high accuracy.

