TSDR: Traffic-Sign Detection and Recognition

——Research Proposal in CS405 Machine Learning

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Background and significance

1.1 TSDR: Traffic Sign Detection and Recognition

• used to identify and interpret various road signs and signals by computer vision.

 a critical component of Intelligent Transportation Systems (ITS), Advanced Driving Assistance Systems (ADAS) and autonomous driving.

1.2 Significance

- reduce the likelihood of accidents by providing drivers with essential information such as road conditions, speed limits, potential hazards and so on
 - over 1.2 million people die across the globe annually due to road accidents.
- as a key component in ADAS and autonomous driving
- help ITS monitor road conditions in real time, adjust traffic signals, and provide traffic information

1.3 Motivations

• its related technologies advance

like computer vision, deep learning & neural networks

has immense commercial value

Market Size and CAGR Estimates (2024-2029)				
Market	Estimated Size (2024)	Estimated Size (2029)	CAGR (2024-2029)	
ADAS Autonomous driving	USD 49.65 billion USD 41.10 billion	USD 107.47 billion USD 114.54 billion	16.70% 22.75%	
ITS	USD 33.38 billion	USD 46.36 billion	6.79%	

Analysis of Current Research Status

2.1 Datasets & Benchmark

Road-sign-detection Dataset:

Contains 877 images across 4 classes for road sign detection.

• CCTSDB (Chinese City Traffic Sign Database) Dataset:

A large-scale dataset with 5183 images of 43 distinct traffic sign types from real-world traffic scenarios in Germany.

• CCTSDB (Chinese City Traffic Sign Database) Dataset:

Contains more than 10,000 images with over 60 categories of Chinese traffic signs.

• TT100k Dataset:

A large-scale traffic sign dataset containing 100,000 images.

2.2 Models Architecture and Principle

color and shape analysis

Feature-Based Methods

Ensemble learning

• The novel deep learning-base method

Color segmentation process eliminates the unnecessary objects and hence it reduces the search area of the image or video frame.









RGB HSI

Pixels of interest in HSI

Binary image

As for the shape analysis, it can eliminate the issue in color based detection is the ambient illumination variation

Color Space	Detection Rate
RGB	88.75%
HSV	95%
HSI	91.35%

more color based detection methods

	Category	Paper	Year	Method	Detected colors
Col		[2]	2010	Normalized RGB thresholding	Red, blue, yellow
	RGB based thresholding	[30]	2010	Color Enhancement	Red, blue, yellow
or B		[31]	2015	Color Enhancement	Red, blue, yellow
Color Based	Hue and saturation	[2]	2010	Hue and saturation thresholding	Red, blue, yellow
	thresholding	[33]	2004	LUTs based HS thresholding	Red, blue, yellow
etec	Thresholding on other	[2]	2010	Ohta thresholding	Red, blue, yellow
Detection	spaces	[34]	2015	Lab thresholding	Red, blue, yellow, green
	Chromatic/Achromatic	[2]	2010	RGB, HIS, Ohta decomposition	white
Methods	Decomposition	[34]	2015	RGB based achromatic segment	white
ods	Pixel classification	[2]	2010	SVM classification	Red, blue, yellow
	r ixer classification	[36]	2012	Probabilistic neural networks	Red, blue, yellow

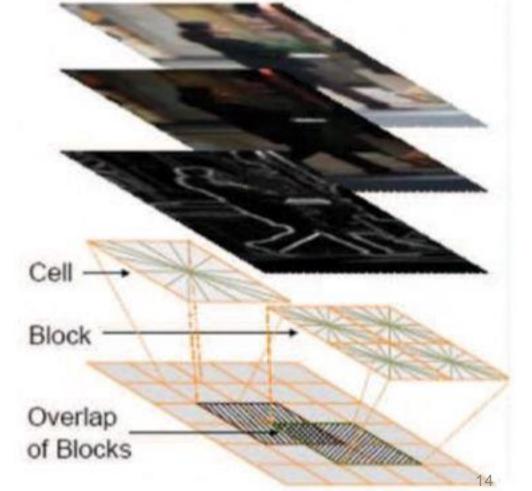
more shape based detection methods

Category	Paper	Year	Method	Detected shapes
	[38]	2015	Hough	Circle and triangle
Shape detection	[39]	2008	Radial symmetry transform	Circle
	[86]	2004	Radial symmetry transform	Polygons
Shape analysis and	[41]	2003	Complex shape models	Circle, polygons
matching	[42]	2008	Shape decomposition	Circle, square, triangle
Fourier	[26]	2011	Fourier descriptors	Circle, square, triangle
transformation	[43]	2008	Fast Fourier Transformation	Circle, square, triangle
Varanainte	[45]	2014	SIFT	Circle, square, triangle, octagon
Key points detection	[15]	2014	Harris corner	Circle, triangle
detection	[46]	2014	Interest points clustering	Different shapes

Feature-Based Methods

This structure utilizes HOG-like features to express the objects and

as an SVM classification problem, in which each candidate is classified into objects or backgrounds.

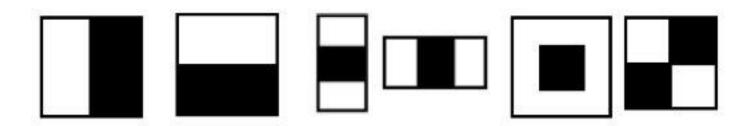


HOG descriptor

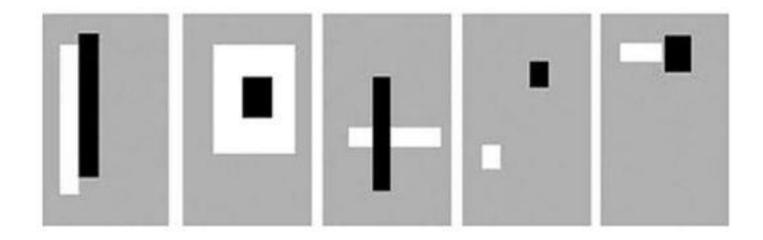
Viola and Jones' AdaBoost and cascade based detection structure (VJ) has been proved very efficient in some object detection problems. The selection of features is crucial for AdaBoost based TSDR detectors.

- Haar-like feature
- Dissociated dipoles feature
- Binary Pattern (MB-LBP) feature

The Haar-like feature can express the gray level difference of traffic signs.

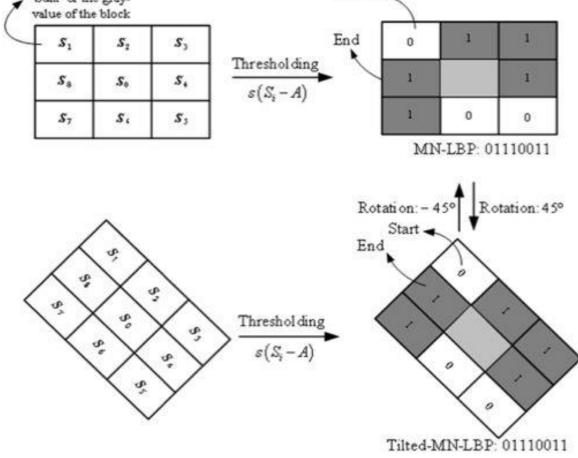


Dissociated dipoles feature is a more general rectangular feature. Using uncon-nected two dipoles, the dissociated dipoles feature can produce more features to express traffic signs.



Multi-block normalization LBP (MN-LBP) features can

express different types of features.



Start

Database Size	Feature	Classifier	Recognition	Remarks	
Database Size	Extractor	Used	Rate (in %)		
	RGB colour segmentation				
	Proposed algorithm	SVM	97.04	Novel idea	
	for circular signs	SVIVI	77.04	110VCI Idea	
3 Signs	1NN each for matching		>95	No proper database	
5 Signs	shape and colour		793	Not applicable in real time	
	Circle by Hough	SURF &			
	Triangle by Ramer-Douglus-	FLAN	85		
	Rucar	12111			
	Traffic sign detection	LDA		Also uses motion	
	Trumo bign detection	2211		information.	
48 signs Polish,Japanese	Equiangular polygons	Gaussian	85.3	Novel idea	

The novel deep learning-base method

The Convolutional Neural network (CNN) based detection methods learn features through convolutional network.

In recent years, with the development of deep learning, many different deep neural network structures have appeared and made breakthrough in different detection areas.

You only look once (YOLO)

Zhang et al. utilized YOLOv2 to design their real-time traffic sign detection method.

Liu et al.[5] use a YOLO CNN to classify traffic signs and MSRCR image augmentation during pre-processing.

Sharma and Kumar's study provides YOLOv8 for traffic signal recognition in the advanced version that takes place in a real time environment for road safety improvement.

Comparison

HOG+LDA [6] 70.33% 35.94% 12.01% N/A Hough-like [6] 26.09% 30.41% 12.86% N/A Viola-Jones [6] 90.81% 46.26% 44.87% N/A HOG+LDA+SVM [89] 100% 99.91% 100% 3.533 ChnFtrs [25] 100% 100% 96.98% N/A HOG+SVM [67] 99.98% 98.72% 95.76% 3.032 SVM+Shape [68] 100% 99.88% 97.62% 12.32 SFC-tree [88] 100% 99.20% 98.57% 0.192 (3.19 GHz CPU) CNN [E-53] 99.89% 99.93% 99.16% 0.162 (Titan x GPU) ACF+SPC+LBP+AdaBoost [58] 100% 99.89% 97.87% N/A AdaBoost+SVR [59] 100% 100% 99.87% N/A AdaBoost+SVR [59] 99.45% 98.33% 96.50% N/A AdaBoost+SVR [59] 93.45% 99.88% 97.78% 0.05-0.5 (Intel Core-i7 A770 CPU) AdaBoost+SVR [59] 39.45% 99.88% 97.78% 0.05-0.5 (Intel Core-i7 A770 CPU) AdaBoost+SVR [59] AP(%): 50.82%(Small), 88.05%(med), 96.82%(large) Faster-RCNN in [72] AP(%): 43.93%(Small), 97.8%(medium), 98.31%(large) Fast R-CNN in [10] Recall: 56%; Accuracy: 50% N/A AN+FRPN [72] AP(%): 43.93%(Small), 97.8%(medium), 98.31%(large) Fast R-CNN in [72] AP(%): 31.22%(Small), 86.9%(med), 96.05%(large) Faster-RCNN in [72] AP(%): 31.22%(Small), 86.9%(med), 96.05%(large) Faster-RCNN in [72] AP(%): 31.22%(Small), 77.17%(med), 94.05%(large) ICF in [11] 87.32% 96.03% 91.09% N/A ACF in [11] 87.32% 96.03% 91.09% N/A ACF in [11] 87.32% 96.11% 96.17% N/A ACF in [11] 99.94 65.09% O.0376 O.128 (Tesla K20 GPU) O.165 (Tesla K20 GPU) 94.05%(large) O.165 (Tesla K20 GPU) ACF in [11] 99.94 96.11% 96.17% N/A O.165 (Tesla K20 GPU) ACF in [11] 99.94 96.11% 96.17% O.165 (Tesla K20 GPU) O.165 (Tesla K20 GPU) 99.05%(large) O.165 (Tesla K20 GPU) ACF in [11] 99.94 96.11% 96.17% O.165 (Tesla K20 GPU) O.165 (Tesla K20 GPU) 99.05%(large) O.165 (Tesla K20 GPU) ACF in [11] 99.94 96.11% 96.11% 96.11% 0.165 (Tesla K20 GPU) O.165 (Tesla K20 GPU) 99.05%	Dataset	Methods	Prohibitive	Danger	Mandatory	Time (s)
Hough-like [6] 26.09% 30.41% 12.86% N/A Viola-Jones [6] 90.81% 46.26% 44.87% N/A HOG+LDA+SVM [89] 100% 99.91% 100% 3.533 ChnFtrs [25] 100% 100% 96.98% N/A HOG+SVM [67] 99.98% 98.72% 95.76% 3.032 SVM+Shape [68] 100% 99.885% 92.00% 0.4-1 SVM+CNN [69] N/A 99.88% 97.62% 12-32 SFC-tree [88] 100% 99.89% 99.78% 0.102 (3.19 GHz CPU) CNN [E-53] 99.89% 99.93% 99.16% 0.162 (Titan X GPU) ACF+SPC+LBP+AdaBoost [58] 100% 98.00% 99.87% N/A AdaBoost+SVR [59] 100% 100% 99.87% N/A AdaBoost+SVR [59] 100% 100% 99.87% N/A AdaBoost+SVR [59] 99.45% 99.33% 96.50% N/A ChnFtrs [25] 94.44% 97.40% 97.96% 1-3 (Intel Core i7 870 CPU, GTX 470 GPU AN+FRPN [72] AP(%): 50.82%(Small), 88.05%(med), 98.31%(large) Faster-RCNN in [72] AP(%): 43.93%(Small), 97.8%(medium), 98.31%(large) T1100k AN+FRPN [72] AP(%): 43.93%(Small), 97.8%(medium), 98.31%(large) Faster-RCNN in [72] AP(%): 49.81%(Small) in [10] N/A AN+FRPN [72] AP(%): 49.81%(Small) in [10] N/A Curves can be found in [10] N/A AN+FRPN [72] AP(%): 49.81%(Small) in [10] N/A AN+FRPN [72] AP(%): 49.81%(Small) in [10] N/A Curves can be found in [10] O.128 (Tesla K20 GPU) of 0.05%(large) Faster-RCNN in [72] AP(%): 31.22%(Small), 71.77%(med), 90.158 (Tesla K20 GPU) of 0.05%(large) Faster-RCNN in [72] AP(%): 31.22%(Small), 71.77%(med), 91.09% (No Turn) ACF in [11] 88.98% 96.03% 91.09% (No Turn) ACF in [11] 89.89% 96.03% 91.09% (No Turn)			(AUC)	(AUC)	(AUC)	
Viola-Jones [6] 90.81% 46.26% 44.87% N/A HOG+LDA+SVM [89] 100% 99.91% 100% 3.533 ChnFtrs [25] 100% 100% 96.98% N/A HOG+SVM [67] 99.98% 98.72% 95.76% 3.032 SVM+Shape [68] 100% 98.85% 92.00% 0.4-1 SVM+CNN [69] N/A 99.78% 97.62% 12.32 SFC-tree [88] 100% 99.20% 98.57% 0.192 (3.19 GHz CPU) CNN [E-53] 99.89% 99.93% 99.16% 0.162 (Titan X GPU) ACF+SPC+LBP+AdaBoost [58] 100% 98.80% 97.57% N/A AdaBoost+SVR [59] 100% 100% 99.87% N/A AdaBoost+CNN+SVM [73] 99.45% 98.33% 96.50% N/A AdaBoost+SVR [59] 93.45% 99.88% 97.78% 1-3 (Intel Core i7 870 CPU, GTX 470 GPU AN+FRPN [72] AP(%): 50.82%(Small), 97.88%(med), 96.82%(large) 0.128 (Tesla K20 GPU) Faster-RCNN in [72] AP(%): 43.93%(Small), 97.88%(medium), 98.31%(large) 0.165 (Tesla K20 GPU) Multi-class Network [10] Recall: 56%; Accuracy: 88%		HOG+LDA [6]	70.33%	35.94%	12.01%	N/A
HOG+LDA+SVM [89]		Hough-like [6]	26.09%	30.41%	12.86%	N/A
ChnFtrs [25] 100% 100% 96.98% N/A HOG+SVM [67] 99.98% 98.72% 95.76% 3.032 SVM+Shape [68] 100% 98.85% 92.00% 0.4-1 SVM+CNN [69] N/A 99.78% 97.62% 12-32 SFC-tree [88] 100% 99.20% 98.57% 0.192 (3.19 GHz CPU) CNN [E-53] 99.89% 99.93% 99.16% 0.162 (Titan X GPU) ACF+SPC+LBP+AdaBoost [58] 100% 98.00% 97.57% N/A AdaBoost+CNN+SVM [73] 99.45% 98.33% 96.50% N/A AdaBoost+CNN+SVM [73] 99.44% 97.40% 97.96% 1-3 (Intel Core i7 870 CPU, GTX 470 GPU AN+FRPN [72] AP(%): 50.82%(Small), 88.05%(med), 96.82%(large) 0.165 (Tesla K20 GPU) Faster-RCNN in [72] AP(%): 43.93%(Small), 97.8%(medium), 96.82%(large) 0.165 (Tesla K20 GPU) AN+FRPN [72] AP(%): 43.93%(Small), 86.9%(med), 96.05% N/A Curves can be found in [10] N/A TIT100k AN+FRPN [72] AP(%): 49.81%(Small), 86.9%(med), 96.05%(large) 0.128 (Tesla K20 GPU) Faster-RCNN in [72] AP(%): 49.81%(Small), 86.9%(med), 96.05%(large) 0.128 (Tesla K20 GPU) Faster-RCNN in [72] AP(%): 31.22%(Small), 77.17%(med), 96.05%(large) 0.165 (Tesla K20 GPU) ACF in [11] 87.32% 96.03% 91.09% N/A LISA ACF in [11] 88.98% 96.11% 96.17% N/A		Viola-Jones [6]	90.81%	46.26%	44.87%	N/A
HOG+SVM [67] 99.98% 98.72% 95.76% 3.032		HOG+LDA+SVM [89]	100%	99.91%	100%	3.533
SYM+Shape [68] 100% 98.85% 92.00% 0.4-1	**	ChnFtrs [25]	100%	100%	96.98%	N/A
SVM+CNN [69] N/A 99.78% 97.62% 12-32 SFC-tree [88] 100% 99.20% 98.57% 0.192 (3.19 GHz CPU) CNN [E-53] 99.89% 99.93% 99.16% 0.162 (Titan X GPU) ACF+SPC+LBP+AdaBoost [58] 100% 98.00% 97.57% N/A AdaBoost+SVR [59] 100% 100% 99.87% N/A AdaBoost+CNN+SVM [73] 99.45% 98.33% 96.50% N/A AdaBoost+CNN+SVM [73] 99.45% 98.33% 96.50% N/A AdaBoost+SVR [59] 93.45% 97.40% 97.96% 1-3 (Intel Core i7 870 CPU, GTX 470 GPU AN+FRPN [72] AP(%): 50.82% (Small), 88.05% (med), 96.82% (large) Faster-RCNN in [72] AP(%): 43.93% (Small), 97.8% (medium), 98.31% (large) Fast R-CNN in [10] Recall: 56%; Accuracy: 50% N/A Curves can be found in [10] AN+FRPN [72] AP(%): 43.91% (small), 86.9% (med), 96.05% (large) Faster-RCNN in [72] AP(%): 49.81% (Small), 86.9% (med), 96.05% (large) Faster-RCNN in [72] AP(%): 31.22% (Small), 86.9% (med), 96.05% (large) Faster-RCNN in [72] AP(%): 31.22% (Small), 86.9% (med), 96.05% (large) Faster-RCNN in [72] AP(%): 31.22% (Small), 77.17% (med), 94.05% (large) LISA ACF in [11] 87.32% 96.03% 91.09% (NoTurn) ACF in [11] 98.98% 96.11% 96.17% N/A	*	HOG+SVM [67]	99.98%	98.72%	95.76%	3.032
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AdaBoost+CNN+SVM [73] 99.45% 98.33% 96.50% N/A		ACF+SPC+LBP+AdaBoost [58]	100%	98.00%	97.57%	N/A
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BTSD AdaBoost+SVR [59] 93.45% 99.88% 97.78% 0.05~0.5 (Intel Core-i7 4770 CPU)	*	AdaBoost+CNN+SVM [73]	99.45%	98.33%	96.50%	N/A
AdaBoost+SVR [59] 93.45% 99.88% 97.78% 0.05~0.5 (Intel Core-i7 4770 CPU)		ChnFtrs [25]	94.44%	97.40%	97.96%	1~3 (Intel Core i7 870
BTSD AdaBoost+SVR [59] 93.45% 99.88% 97.78% 4770 CPU) AN+FRPN [72] AP(%): 50.82%(Small), 88.05%(med), 96.82%(large) 0.128 (Tesla K20 GPU) Faster-RCNN in [72] AP(%): 43.93%(Small), 97.8%(medium), 98.31%(large) 0.165 (Tesla K20 GPU) Fast R-CNN in [10] Recall: 56%; Accuracy: 50% N/A Curves can be found in [10] N/A Curves can be found in [10] AP(%): 49.81%(Small), 86.9%(med), 96.05%(large) 0.128 (Tesla K20 GPU) Faster-RCNN in [72] AP(%): 31.22%(Small), 77.17%(med), 94.05%(large) 0.165 (Tesla K20 GPU) ICF in [11] 87.32% 96.03% 91.09% N/A LISA ACF in [11] 98.98% 96.11% 96.17% N/A						CPU, GTX 470 GPU
AN+FRPN [72] AP(%): 50.82%(Small), 88.05%(med), 96.82%(large) 0.128 (Tesla K20 GPU) Faster-RCNN in [72] AP(%): 43.93%(Small), 97.8%(medium), 98.31%(large) 0.165 (Tesla K20 GPU) Fast R-CNN in [10] Recall: 56%; Accuracy: 50% N/A Curves can be found in [10] Multi-class Network [10] Recall: 91%; Accuracy: 88% N/A Curves can be found in [10] AN+FRPN [72] AP(%): 49.81%(Small), 86.9%(med), 96.05%(large) Faster-RCNN in [72] AP(%): 31.22%(Small), 77.17%(med), 94.05%(large) ICF in [11] 87.32% 96.03% 91.09% N/A LISA ACF in [11] 98.98% 96.11% 96.17% N/A	BTSD -	AdaBoost+SVR [59]	93.45%	99.88%	97.78%	
Faster-RCNN in [72] 98.31%(large) 0.165 (Tesla K20 GPU)		AN+FRPN [72]				0.128 (Tesla K20 GPU)
TT100k Curves can be found in [10] N/A		Faster-RCNN in [72]			0.165 (Tesla K20 GPU)	
TT100k AN+FRPN [72] AP(%): 49.81%(Small), 86.9%(med), 96.05%(large) Faster-RCNN in [72] AP(%): 31.22%(Small), 77.17%(med), 94.05%(large) ICF in [11] 87.32% (Diamond) (Stop) ACF in [11] ACF in [11] Curves can be found in [10] AP(%): 49.81%(Small), 86.9%(med), 96.05%(large) 0.128 (Tesla K20 GPU) 0.165 (Tesla K20 GPU) N/A N/A ACF in [11] 98.98% 96.11% 96.17% N/A		Fast R-CNN in [10]			N/A	
AN+FRPN [72] AP(%): 49.81%(Small), 86.9%(med), 96.05%(large) O.128 (Tesla K20 GPU) Paster-RCNN in [72] AP(%): 31.22%(Small), 77.17%(med), 94.05%(large) O.165 (Tesla K20 GPU) N/A ACF in [11] AP(%): 49.81%(Small), 86.9%(med), 96.05%(large) O.165 (Tesla K20 GPU) N/A N/A	TT1001	Multi-class Network [10]	2 2			N/A
10.165 (1esia K20 GPU) 10.165 (1esia K20 G	11100K	AN+FRPN [72]				0.128 (Tesla K20 GPU)
LISA (Diamond) (Stop) (NoTurn) N/A ACF in [11] 98.98% 96.11% 96.17% N/A		Faster-RCNN in [72]				0.165 (Tesla K20 GPU)
ACF in [11] 98.98% 96.11% 96.17% N/A	LICA	ICF in [11]	V2071 6000	Weg ce		N/A
(Diamond) (Stop) (NoTurn)	LISA	ACF in [11]	98.98% (Diamond)	96.11% (Stop)	96.17% (NoTurn)	N/A

C. Liu, S. Li, F. Chang and Y. Wang, "Machine Vision Based Traffic Sign Detection Methods: Review, Analyses and Perspectives," in IEEE Access, vol. 7, pp. 86578-86596, 2019, doi: 10.1109/ACCESS.2019.2924947.

Reproduction of Current Paper

Zhang, J., Huang, M., Jin, X., & Li, X. (2017). A real-time Chinese traffic sign detection algorithm based on modified YOLOv2. Algorithms, 10(4), 127

Sanyal, B., Mohapatra, R. K., & Dash, R. (2020, January). Traffic sign recognition: A survey. In 2020 International Conference on Artificial Intelligence and Signal Processing (AISP) (pp. 1-6). IEEE.

Completed Work

3.1 Model Selection

• Deep learning revolution in TSDR:

Traditional machine learning: SVM, KNN, HOG ---> CNN.

Advantages of YOLO:

Balance of speed and accuracy

Transfer learning

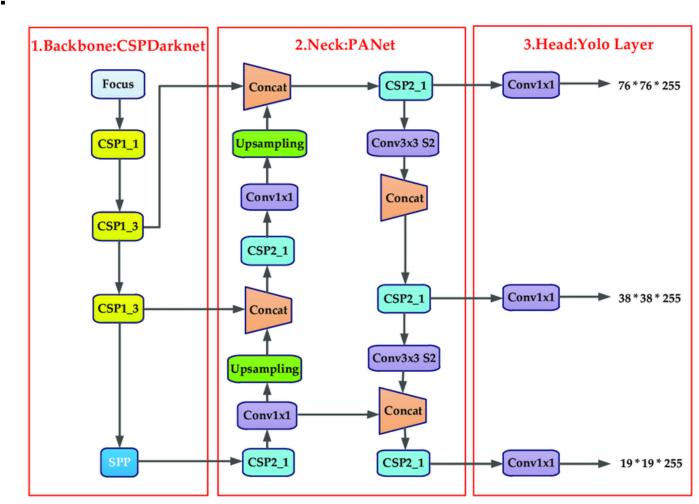
Flexibility for deployment

3.2 Model Principle

Architecture:

Traditional machine learning:

SVM, KNN, HOG ---> CNN.



3.2 Model Principle

- **Backbone**: The backbone network extracts features from the input image. YOLOv5 uses CSPDarknet53 as its backbone, a variant of Darknet53 that introduces Cross-Stage Partial Networks (CSP) to enhance feature propagation and reduce the computational load.
- **Neck:** The neck in YOLOv5 uses the PANet (Path Aggregation Network) to combine feature maps from different layers, allowing the model to leverage both low-level and high-level features. This helps the model make more accurate predictions, especially for small or distant objects.
- **Head:** The head of the network is responsible for making the final predictions (bounding box, class probability, and object confidence) from the features extracted by the backbone and aggregated by the neck.

• s m l x x6

3.3 Experiment result

Dataset:

Road Sign Detection dataset, 877 images of 4 distinct classes (https://www.kaggle.com/datasets/andrewmvd/road-sign-detection/data)

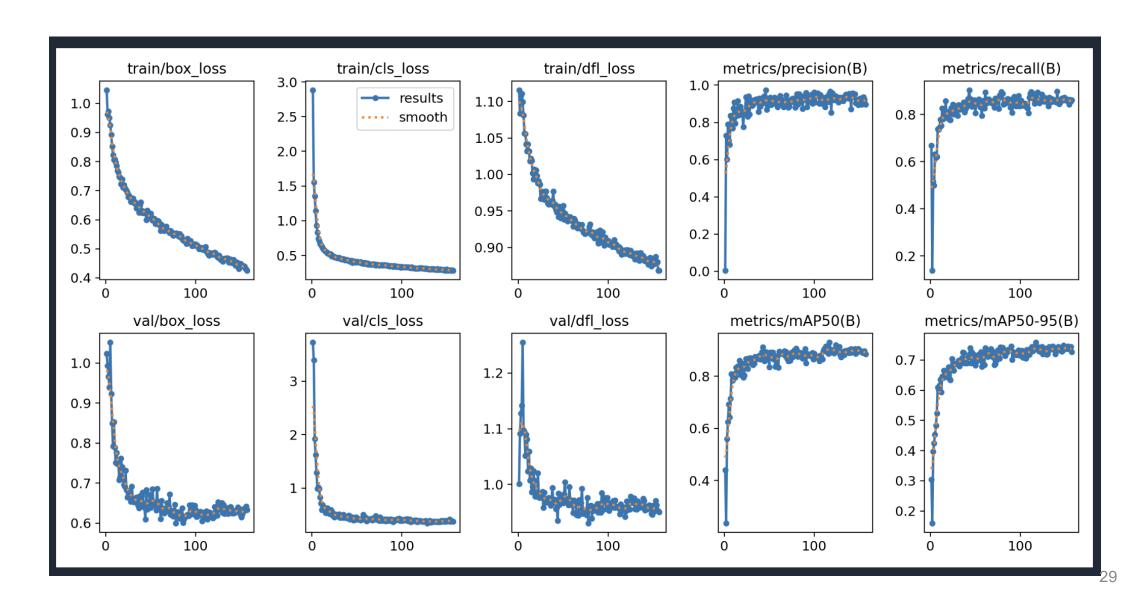
Result:

mAP 93.1%

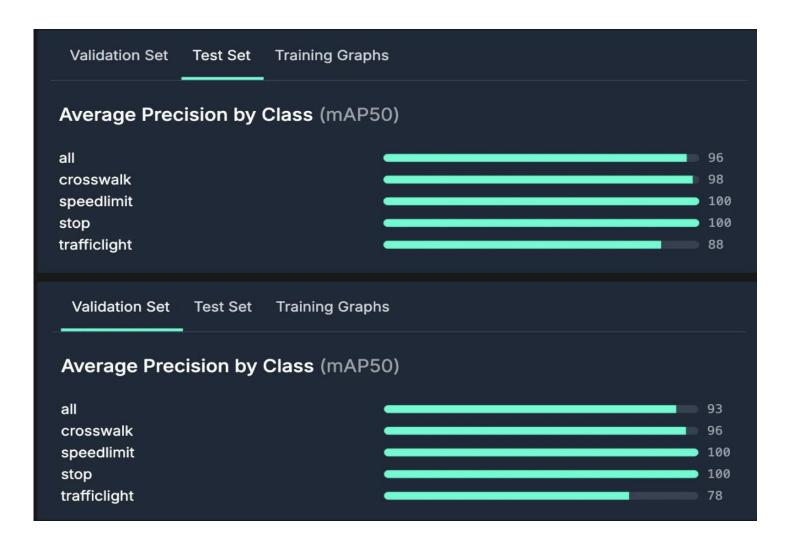
Precision 95.5%

Recall 87.6%

3.3 Experiment result



3.3 Experiment result





Research Plan and Expected Results

4.1 Time schedule

2024/10/24 week 7	Project selection: TSDR problem (Traffic Sign Detection and Recognition)
2024/11/11 week 8	Midterm Preparation
2024/11/7 week 9	Reproduce provided reference paper indivizually. Read field background information and the latest paper overview. Collect dataset, test different methods and models.
2024/11/14 week 10	Make comparision from previous work. Choose yolov5 as the base model of the project.

2024/11/21 week 11	Train yolov5's branch models on collected dataset. Analyse the training results.
2024/11/28 week 12	Do Research Proposal and PPT. Summarize previous work and make plan for the following weeks.
2024/12/5 week 13	Clean the tt100k dataset and transform it to YOLO format and train it on the YOLOv5 models. Compare experiment results with previous paper and work, try to do optimization and add some plug-and-play modules to the chosen model. Analyse the difference and disscuss further work.
2024/12/12 week 14	Training final optimized model and implement it on the device. Test it in real life and analyse the result. Disscuss the further improvement in terms of real life implementation.
2024/12/19 week 15	Write final report and prepare for the presentation

4.2 Expected results

Use YOLO to do regression and use Sill-net to do light optimization and do reclassification to achieve better accuracy compared with present results.

Add attention mudule(time, space, frequency...) to YOLO, in order to increase the accuracy of classification.

The expected performance is to be able to process realworld traffic sign images or video streams by 30 fps on a mobile phone device.

Potential Challenges and Solutions

5.1 Data Challenge

Illumination Issues

Motion Blur

Perspective Issues

Partial Occlusion



Illumination



Perspective



Blur



Occlusion

5.2 Architecture Challenges

- Dataset Limitations
- Model Complexity
- Overfitting Risk
- Real-Time Performance
- Integration with Real-World Systems
- Dynamic Environment Adaptability

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