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Deep Learning for Image-based Automatic Dial Meter Reading: Dataset and Baselines

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Automatic Meter Reading

- Easy/Cheap to deploy
- Enables the possibility of self-reading
- Solution for rural/remote areas
- Reduce the number of errors in readings
- Produces a proof of reading for verification

Source: https://anyline.com/news/customer-meter-reading-app/

Energy Meters

cyclometer display

dial display

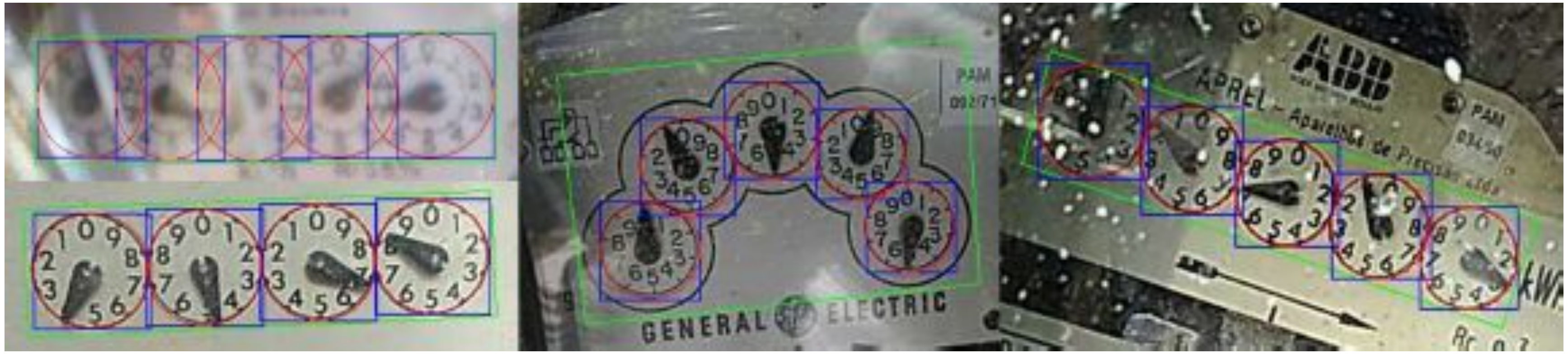
electronic display

smart meter

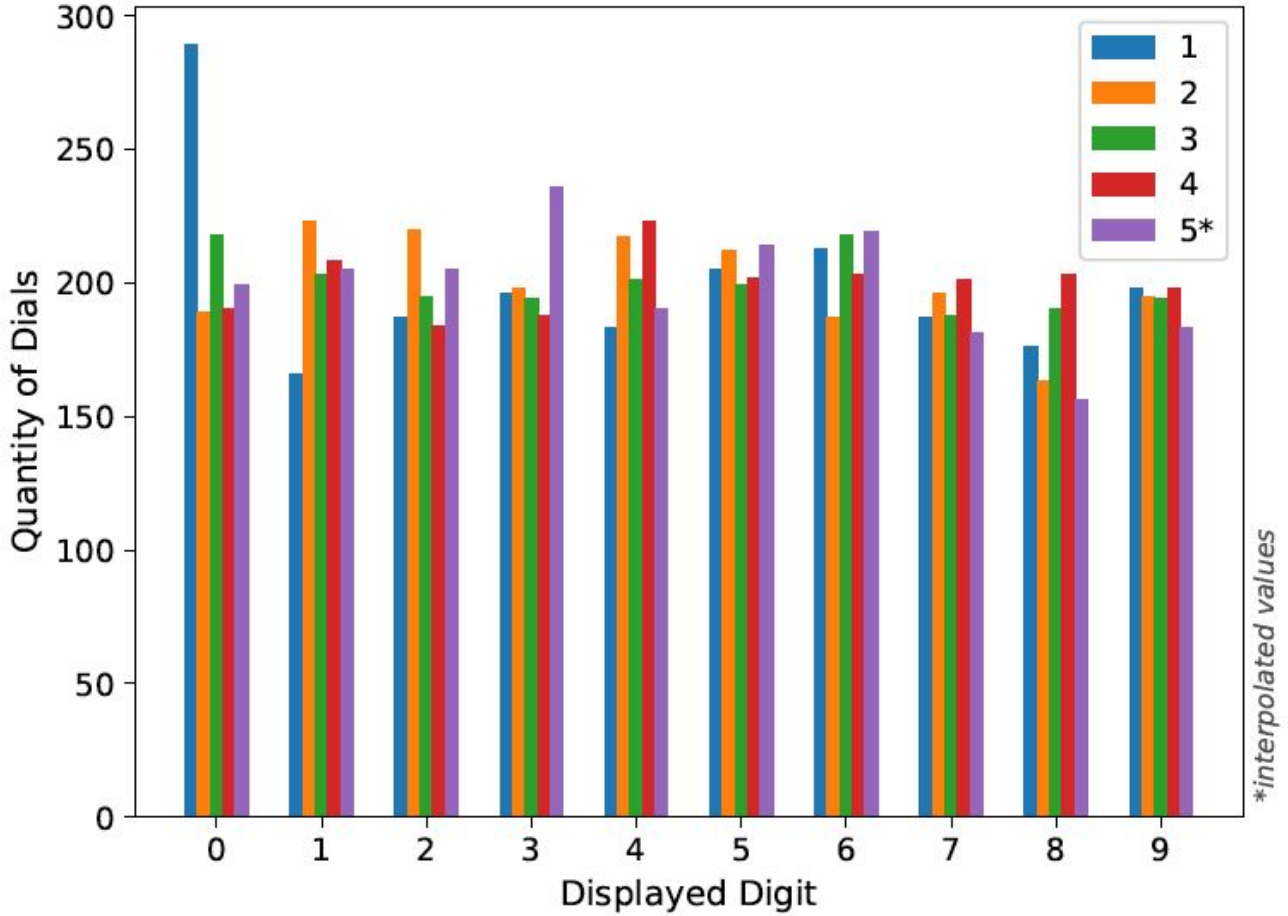
ADMR-UFPR Dataset

ADMR-UFPR Dataset

- 2,000 fully annotated unconstrained real-world dial meter images
- Publicly available (shared only upon request)
- 4 or 5 dials per meter (45% of 4, 55% of 5)



Dataset Digit Distribution



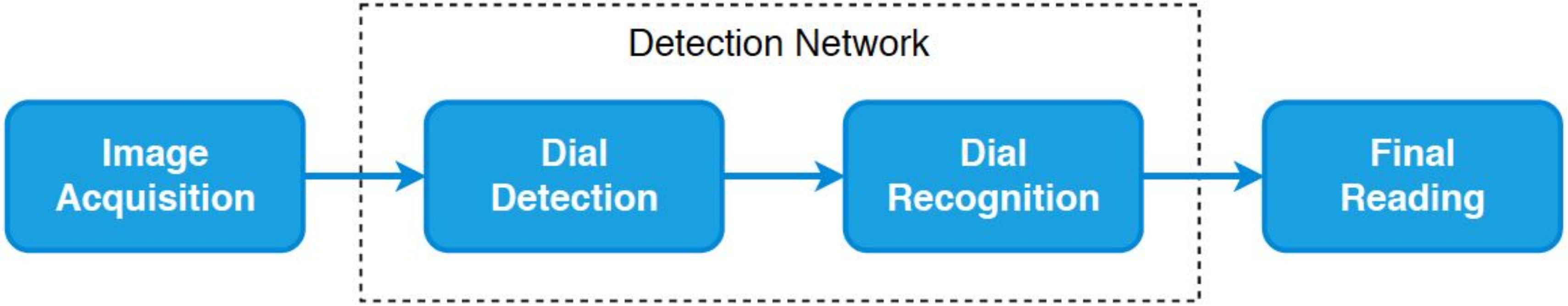
Dataset Challenging Conditions

- Uneven lighting
- Blur
- Distant capture
- Reflections
- Dirt
- Glare
- Broken glass

Proposed Pipeline

We evaluate two detection networks:

- YOLO (v2, v3, Fast-YOLO variants)
- Faster R-CNN (ResNet-50, ResNet-101, ResNeXt-101)



Experimental Protocol

The dataset is divided into three subsets:

- 1200 images for training (60%)
- 400 images for validation (20%)
- 400 images for testing (20%)

Metrics:

- Meter Recognition Rate
- Dial Recognition Rate (Edit distance)
- Mean Absolute Error

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IET
The International Neural Network Society (INNS)
EPS Evolutionary Programming Society

Detection Results

Detection Model	Backbone		(%)	
		Prec.	Recall	F-score
Hough Circle Transform	-	53.27	55.28	54.25
Fast-YOLOv3	Darknet	99.94	100.0	99.97
YOLOv3	**Darknet-53**	**100.0**	**100.0**	**100.0**
Faster R-CNN	ResNet-50	100.0	99.94	99.97
Faster R-CNN	**ResNet-101**	**100.0**	**100.0**	**100.0**
Faster R-CNN	**ResNeXt-101**	**100.0**	**100.0**	**100.0**

Recognition Results

Method	Input Size	FPS	Recognition (%) Dial	Recognition (%) Meter	Mean Abs. Error
Fast-YOLOv2	416×416	**244**	79.61	42.25	5382.06
Fast-YOLOv2	608×608	145	85.24	51.75	3810.34
Fast-YOLOv3	416×416	220	83.27	47.75	6098.27
Fast-YOLOv3	608×608	120	86.60	54.25	5183.82
YOLOv2	416×416	67	91.42	68.00	2615.23
YOLOv2	608×608	40	92.51	71.25	1924.98
YOLOv3	416×416	35	93.00	73.75	1685.98
YOLOv3	608×608	20	93.38	74.75	1591.16
FR-CNN R-50	800×800	13	92.56	72.25	1451.81
FR-CNN R-101	800×800	11	92.62	71.75	**1343.29**
FR-CNN X-101	800×800	6	**93.60**	**75.25**	1591.77

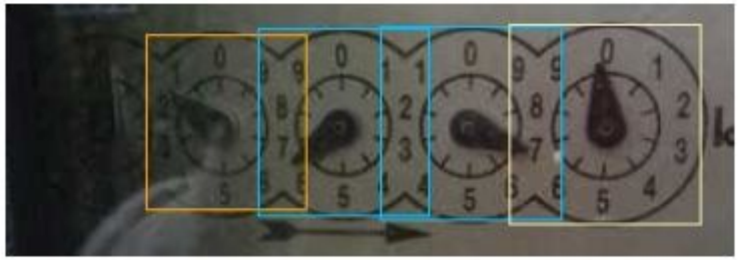
Error Analysis

The most common errors in the presented approach are caused by:

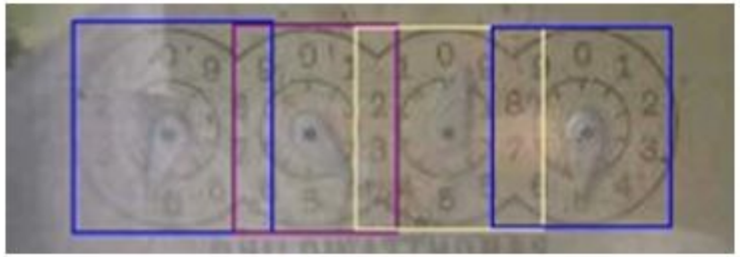
Type of Error	Frequency	
	YOLOv3	Faster X-101
Symmetry	2%	3%
Neighbor value	82%	85%
Severe lighting conditions/Dirt	14%	9%
Rotation	2%	3%

Error Samples

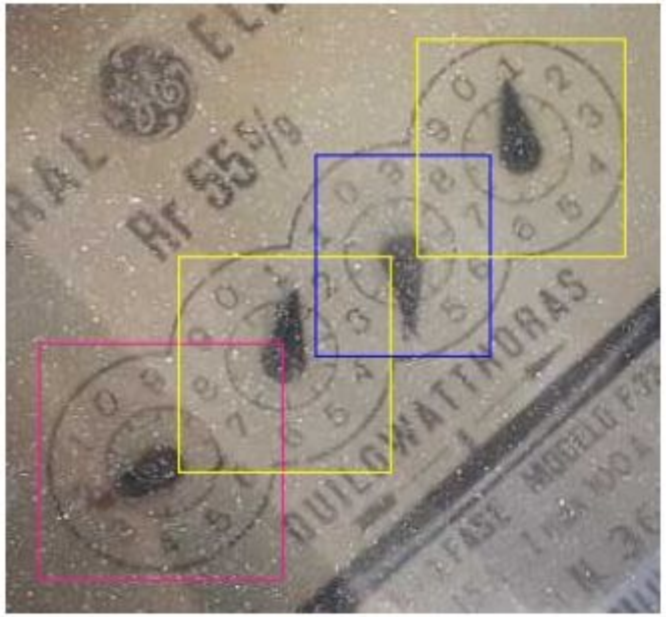
a) 4062
3061 (lev=2)



b) 01669
_1669 (lev=1)



c) 4395
5495 (lev=2)



d) 2140
3050 (lev=3)

Conclusion and Future Works

- New dataset for the research community
- New approaches towards ADMR
- New well-defined protocol for evaluation of ADMR systems

- Address the neighbor errors issue
- Use confidence to eliminate uncertain predictions
- New loss functions to penalize errors on leftmost dials

Acknowledgements

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