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Date : 27/05/2021

Research Paper Reviews-Part 3

Paper-10:

Research on Defect Detection Method for Steel Metal Surface based on Deep Learning

Published Year :2020

Objective :

To detect metal surface defects using improved VGG16 based object detection.

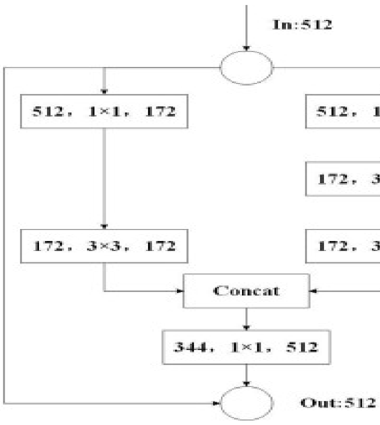
Methodology :

Metal defects can be recognized by modified VGG16 architecture.

Modification :

VGG16 has 5 convalutional blocks. 4th convalutional block is modified with new design block.

New design block consist of Residual networks and inception blocks .



Above block is a new block which replaces the 4th convalutional block in VGG16.

Training Parameters :

Initial learning rate : 0.01
Batch size : 128
momentum :0.9

Performance:

Algorithm model	*AP*	*recall*	*MAP*
VGG foundation model	63%	67%	65%
The improved network model	74%	80%	77%

Conclusion :

Modified VGG16 gives around 77% MAP. In this paper they have used only 1400 data. If dataset is increased , accuracy also increased above 90%.

Paper – 11
Recognition Method of Aerial Insulator Defects Based on Deep Learning

Published Year :2020

Objective :
To detect insulators(Small objects) in tranmission line with YOLOv3 and Asymmetric Convalutional Block.

Methodology:
Insulator is detected by YOLOv3 with modified structure. In YOLOv3 , Darknet-53 act as convalutional block. In New structure replaces Darknet-53 with Asymmetric Convalutional Block(ACB). ACB means it perform covalutional operation with three kernel 1x1, 1x3,3x1 and sums up these ouputs.

K-means++ is used for clustring operation . Up-sampling and residual blocks are used for increase accuracy and avoid gradient vanishing , exploding problem.

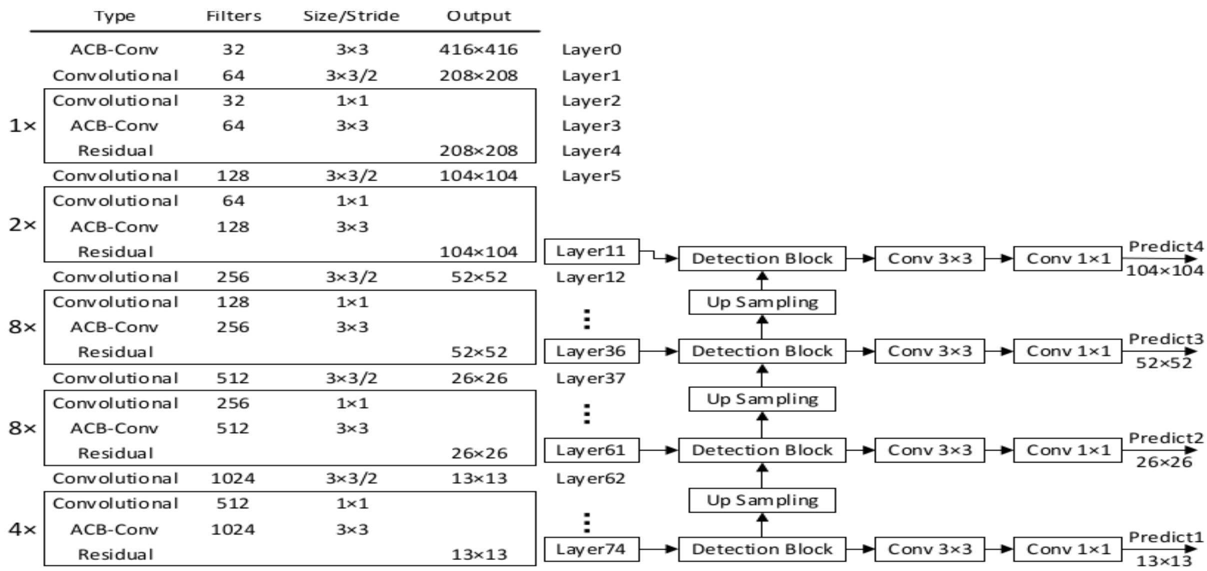


Table 1. Combined with ACB network model comparison

Testing framework	Network model	P/ Insulator	P/ Defect	mAP	Detection speed /FPS
YOLOv3	Darknet-53	85.5	83.7	84.5	33.2
	ACBnet-53	**86.7**	**85.4**	**86.1**	**33.9**
Tiny-YOLO	Tinynet	79.3	77.2	78.3	51.2
	ACBtinynet	**81.4**	**79.9**	**80.7**	**51.1**

Conclusion :

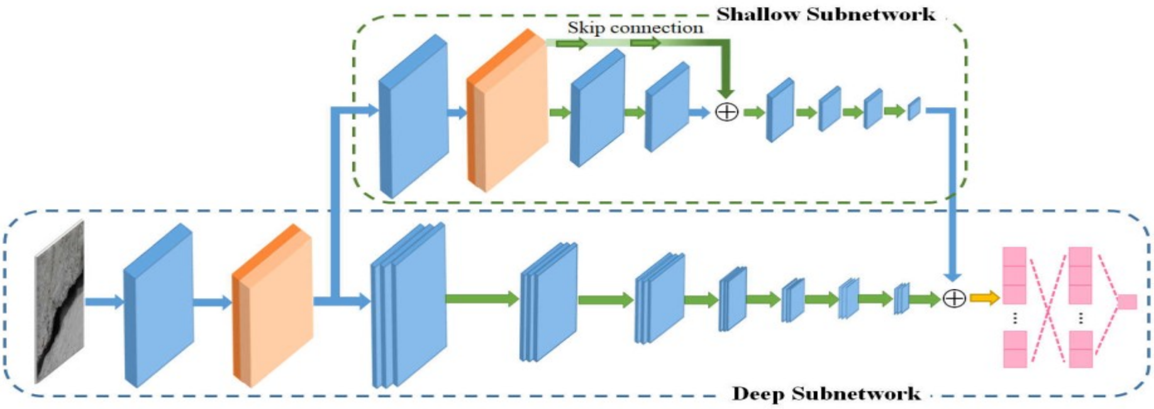
ACBnet-53 gives more good accuracy and speed with compared to Darknet-53. This model is very helpful for detecting small objects in inspection.

Paper - 12:
Detection Of Concrete Cracks Using Dual-channel Deep Convolutional Network

Published Date : 3rd July ,2020

Objective :
To recognize concrete cracks using Dual Channel Convalutional Neural Networks(DuCCnet).

Methodology:
Dual-channel CNN is used to recognize even small cracks in an image. Dual-channel means Sub-architecture is additionally added to main CNN architecture.



In sun-network, the skip connection is used to avoid gradient vanishing and exploding problem. Sub-network act as a residual block for main CNN. Finally two outputs are added together.

Authors tried more model before getting this architecture , The following table shows comparison.

TABLE II. ABLATION STUDY OF THE PROPOSED MODEL

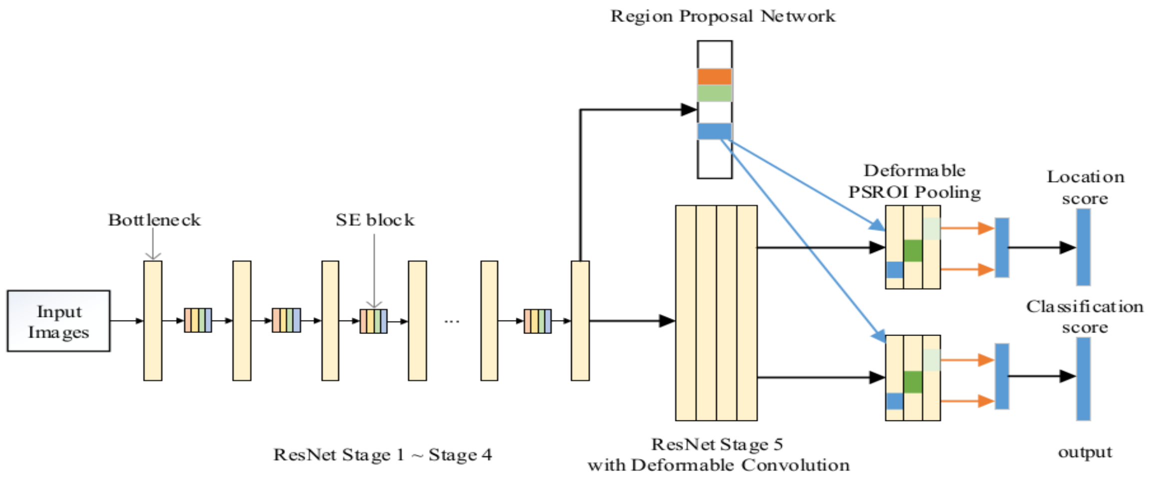
	Model 1	Model 2	Model 3	Model 4	DuCCNet
Channel 1	✓	✓	✓	✓	✓
Channel 2	×	×	✓	✓	✓
Skip Connection	×	×	✓	×	✓
Conv-block7	×	✓	×	✓	✓
Accuracy	79.75	82.50	85.75	89.00	***92.25***

Conclusion:
DuCCNet gives around 92.25 % accuracy. It is good accuracy. Over-fitting is avoided by this Sub-Network.

Paper – 13 :
Transmission Line Image Object Detection Method Considering Fine-Grained Contexts

Published Year :2020
Objective :
To detect Transmission Line components using Region-based Fully Convalutional Neural Networks(R-FCN).

Methodology :
Normal R-FCN architecture with little modification is used for object detection.
Modification :
In R-FCN, Main CNN architecture is build with ResNet50. Squeeze-and-Excitation Blocks(**SE Blocks**) are used in between of ResNet blocks for extract more features. **Deformable Convalutionals** and Position Sensitive Region Of Interest Pooling(**PSROI)** is used in 5^{th} stage of ResNet.



Performance:

Algorithms			
R-FCN	✓	✓	✓
Deformable Convolution		✓	✓
SE blocks			✓
AP@0.5 of Electrical Fittings			
Insulator Strings	89.26%	**90.13%**	89.83%
Fittings of Suspension Conductor	85.73%	**87.29%**	87.18%
Fittings of Tension Conductor	84.52%	84.45%	**86.78%**
Fittings of Suspension Ground Wire	88.25%	86.03%	**88.57%**
Fittings of Tension Ground Wire	79.89%	**83.63%**	82.30%
Ground-wire Insulators	72.12%	74.37%	**74.99%**
Dampers	84.85%	87.25%	**87.69%**
Grading Rings	66.87%	**69.83%**	69.58%
AP@0.5 of Transmission Line Defects			
Spontaneous Explosion of Insulators	95.19%	97.25%	**97.39%**
Faults on Discharge Gaps	72.06%	75.31%	**77.98%**
Damaged Dampers	51.98%	59.49%	**65.40%**
Slipped Dampers	81.30%	86.25%	**86.94%**
Bird Nests	65.65%	68.10%	**72.34%**
Tilt Ground-wire Clamps	72.24%	76.83%	**78.38%**
mAP	77.85%	80.44%	**81.81%**

Conclusion:
This method takes advantages of deformable convolutional layers and SE blocks to improve 3.96% AP by making better use of context information than similar other method.

Paper -14 :
A Drone Based Transmission Line Components Inspection System with Deep Learning Technique

Published Date :30th June,2020

Objective :
To identify the faults of Transmission line components using Deep learning.

Methodology:
Normal YOLOv3 is used for Object detection.
Various AI techniques and Image processing is used for fault analysis.

AI Techniques and Image Processing:
Color clustering based segmentation
Template Matching
Image Eroding
K-means Clustering
Gaussian Mixer
Edge Detection
Ellipse Detection

Performance:

Components Type				YOLO V3		YOLO V3 (Multi-Scaling Removed)	
	#Train Samples	#Test Samples	Total #Samples	Precision (%)	Recall (%)	Precision (%)	Recall (%)
Transmission-tower	4002	1458	5460	80.86	84.03	81.81	85.46
Spacer	2692	464	3156	78.87	86.93	81.9	92.96
Balisor	316	82	398	100.00	100.00	100.00	100.00
Lightning-arrester	2982	454	3436	83.91	89.42	84.93	90.75
PorSTI-W+ PorSTI-R	7404	990	8394	91.87	97.07	93.42	97.47
Insulator (polymer)	800	48	848	92.23	95.36	93.35	96.21
Damper-weight	4088	352	4440	77.19	75.00	79.83	81.45
Sag adjuster	1830	334	2164	71.85	86.64	75.45	87.2
Avg.	24,114	4182	28,296	84.60	89.31	86.34	91.44

Conclusion:

In this paper various computer vision techniques are used to effectively analyze faults of transmission line components. In YOLOv3 , after removing muti-scale model performance little bit increased.