Literature Review

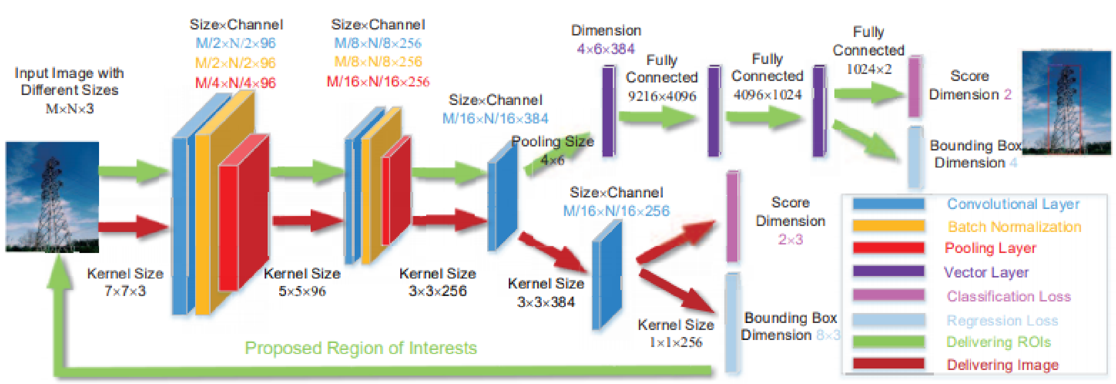
Paper: 1

A Novel Monocular-based Navigation Approach for UAV Autonomous Transmission-line Inspection

The paper implies their main approach is to provide great flexibility for refined inspection and effectively improves inspection safety. In the whole system in a real-world transmission-line inspection scenario under different weather condition and achieve an encouraging result

Problem statements:

1. To locate the effective landmark – transmission tower timely and reliably, they customize a neural network for tower detection and combine it with a fast and smooth tracking.
2. To provide UAV with a robust and precise heading, to detect the transmission lines and compute and optimize their vanishing point.
3. To keep a safe distance from transmission lines, they optimize a homography matrix to restore the parallel nature of transmission lines and perceive the distance variation by a point set registration model.



The tower is regarded as a landmark and robustly located by a customized DL-based Tower R-CNN. Vanishing Point of Power Transmission Lines is calculated and optimized by the Levenberg-Marquardt algorithm used.

Detection Method	Average Precision	Frame Per Second
Faster R-CNN (VGG16)	89.6%	0.8
Faster R-CNN (ZF)	89.5%	2

SSD300	88.9%	6
SSD512	89.2%	2
YOLOv2	86.8%	5.6
Tower R-CNN	89.6%	5

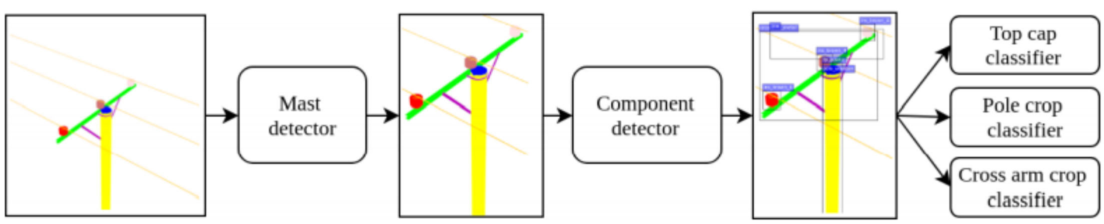
Paper: 2

Intelligent Monitoring and Inspection of Power Line Components Powered by UAVs and Deep Learning

This paper presents a novel automatic autonomous vision based power line inspection system that uses UAV inspection as the main inspection method, optical images as the primary data source, and deep learning as the backbone of the data analysis.

Problem statements:

1. The lack of training data
2. Class imbalance
3. The detection of small components and faults.



Methodology used:

They build their own dataset for training component detection and classification models. And then applied the data augmentation techniques to balance out the imbalanced classes. Finally, they propose multi-stage component detection and classification based on Single Shot Multibox detector(SSMD) and deep Residual Networks (D-ResNet) to detect small components and faults. The model shows the defects on power line components including missing top caps, cracks in poles and cross arms, woodpecker damage on poles, and rot damage on cross arms.

Compared with simple SSD detectors and ResNet50 classifiers, the proposed pipeline with data augmentation achieves 1.2% improvement in terms of mAP on the component detection task; using augmented data to balance out the imbalanced classes improves score in the pole crop classification and cross arm crop classification tasks by 8.7% and 2% respectively.

Paper: 3

Unmanned aerial vehicle vision-based detection of powerline poles by cpu-based Deep learning method

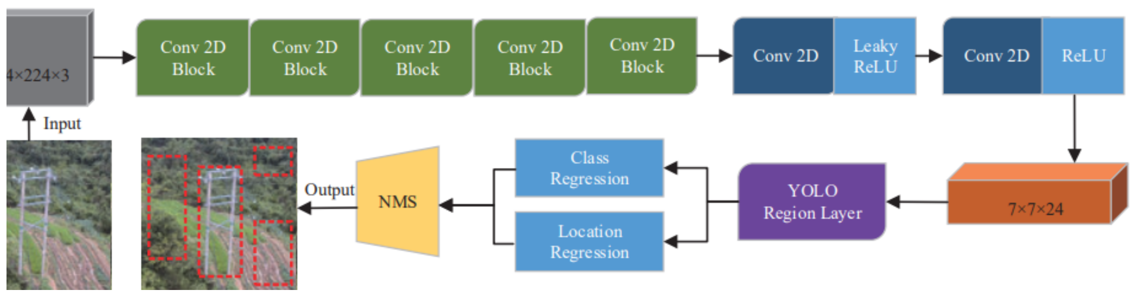
Methodology used :

Yolo-lite, for images recognition HOG algorithm

In this paper they presented the detection model for abnormal line poles from the UAV vision data.

This process they divided into two parts:

1. Generating boxes of poles based on the yolo-lite model.
2. Filter the background boxes based on classification of spatial pyramid pooling model structure.



This model achieves a detection precision of 75.80%, an increase of 26.85% compare to the yolo-lite model alone. The combined poles detection for processing video streaming on a cpu-only computer.

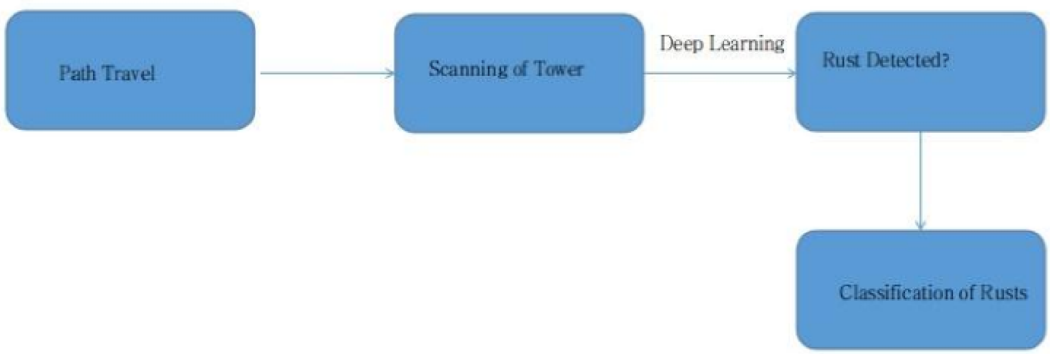
Paper 04:

Automated Inspection of Monopole Tower using Drones and Computer Vision.

In this paper they approach the rust and crack detection formed in monopole towers and also estimate its length and breadth. This paper lies in the real time detection of cracks and saving the altitude for further rectification. Also, edge identification allowed for greater distinction. As a result they successfully detected black, brown, red and yellow rust using tensorflow with 90% accuracy.

For image processing they used openCV for integrating ROS and analyzing images in real time. For crack detection, Haar cascade classifier is used and computer vision is for rust detection.

Figure 4.1. Crack detection system



In the results this system measures the detected cracks, and classifies the types of rusts found using Deep Learning Techniques.

Paper 05:

Development of UAV System for Autonomous Power Line Inspection.

The objective of this paper is a new UAV system for autonomous inspection of electrical energy transmission and distribution networks. The hardware and software configurations, as well as the inspection concept realized into the developed quadrotor helicopter based system were briefly reported. The developed GUI allows easily and safely to set the inspection plan.

In results full inspection of the transmission lines together with towers could be automatically performed. In the autonomous inspection presented in this paper it can be successfully positioned at some lateral offset to allow image acquisition of both sides of the wires.

Methodologies used in this paper are Computer vision techniques for transmission towers recognition, for detection of power transmission lines based on Pulse-Coupled Neural Network.

Paper 06:

High-Voltage Power Transmission Tower Detection Based on Faster R-CNN and YOLO-V3.

Automatic detection and classification of the power towers is the prerequisite for automatic inspection. Automatic inspection by robots or UAVs for the power transmission infrastructures is an essential way to ensure the safety of power transmission.

In this paper they compare two state-of-art deep learning methods to realize the high-voltage power transmission tower detection. dataset of the power towers for multi-object detection, including data collection, preprocessing and annotation is customised.

The models of YOLO-v3 and Faster R-CNN are used to solve multi-object detection on the collected dataset. The performances of the two models are evaluated under different indicators. It is verified that Faster R-CNN has a better detection performance in accuracy. However, the detection speed of the YOLO-V3 model is faster and can be used in real-time detection. Used Matlab to expand and enhance the dataset.

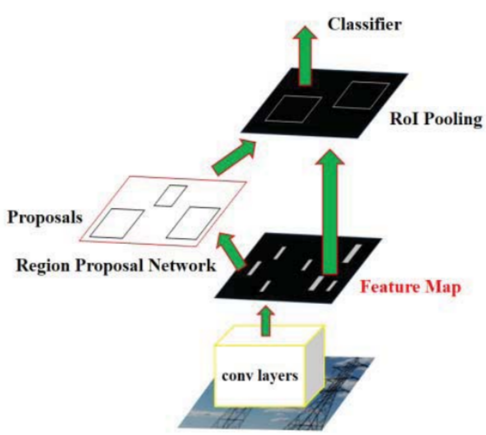


Fig. 3: The structure of Faster R-CNN

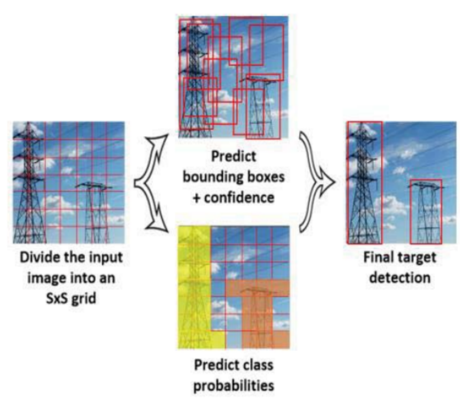


Fig. 4: The method of YOLO detection

Table 2: Confusion matrix of Faster R-CNN model

Predicted class \ Actual class	Drum shape	Umbrella shape	Wineglass shape	Cathead shape
Drum shape(%)	100	0	0	0
Umbrella shape(%)	0	100	0	0
Wineglass shape(%)	0	0	94	4
Cathead shape(%)	0	0	6	96

Table 3: Confusion matrix of YOLO-V3 model

Predicted class \ Actual class	Drum shape	Umbrella shape	Wineglass shape	Cathead shape
Drum shape(%)	96	2	2	2
Umbrella shape(%)	4	98	2	0
Wineglass shape(%)	0	0	88	6
Cathead shape(%)	0	0	8	92

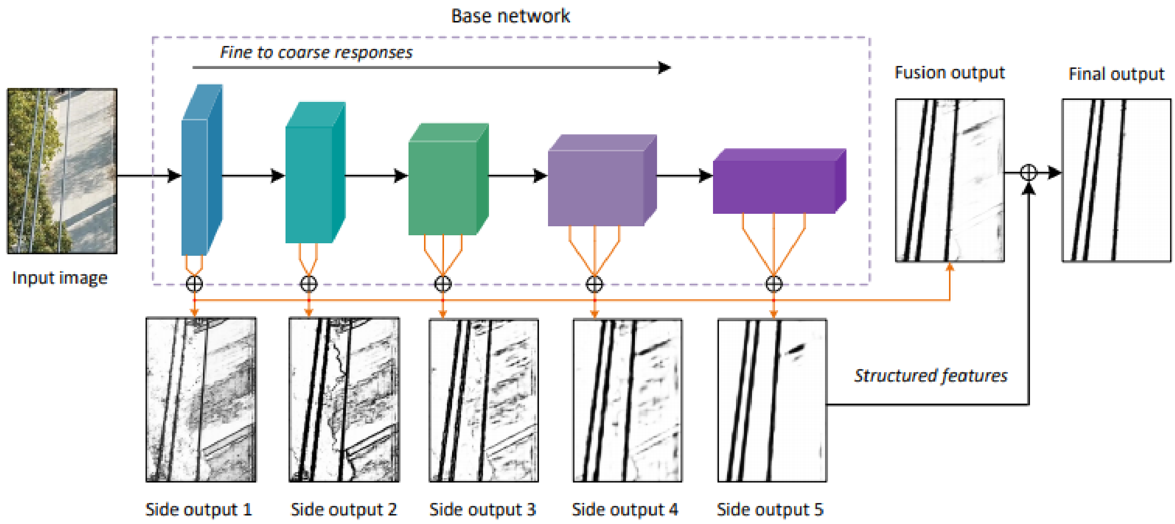
Table 1: Detection Indicators of Two Models

Model Types \ Detection indicators	Average IoU	Average time （s）
Faster R-CNN	0.882	2.136
YOLO-V3	0.874	0.0215

Paper 07

Combined convolutional and structured features for power line detection in UAV images.

Power line detection plays an important role in automated UAV inspection systems, which is crucial for real-time motion planning and navigation along power lines. To overcome from the traditional filters and gradients may fail to capture complete power lines due to noisy backgrounds. This method develops an accurate power line detection method using rich convolutional and structured features.



In this paper, it accomplishes deep supervised neural networks and structured features, for accurate power line detection from UAV images.they used customized two datasets with pixel-level annotations for evaluation. Leveraging hierarchical and structured features, the method produces both accurate and efficient results, which makes it possible to be applied in practice on UAV onboard platforms.
Datasets : https://github.com/SnorkerHeng/PLD-UAV

Table 1. The comparison with baselines on two datasets

Method	PLDU		PLDM	
	ODS	OIS	ODS	OIS
Ours	**0.914**	**0.938**	**0.888**	**0.902**
RCF	0.907	0.931	0.865	0.893
SE	0.850	0.898	0.351	0.340
Gestalt Grouping	0.629	0.629	0.808	0.808
LSD	0.593	0.593	0.796	0.796
Crisp	0.535	0.622	0.641	0.752
Canny	0.466	0.643	0.796	0.866

Paper 08

Power Transmission Lines Inspection using Properly Equipped Unmanned Aerial Vehicle (UAV)

This paper focuses on providing an automated way for fault detection at the Hellenic Electricity Distribution Network that will help on the network maintenance, especially in areas that are not easily accessible by humans.This task can be performed in a low-cost way using unmanned aircrafts

They examine the effectiveness of using basic image processing methods on image data of the power lines acquired by an unmanned aerial vehicle (UAV).
Two methodologies are proposed

1. Power transmission lines detection using Hough transform
2. Regions of Interest Definition using Image information

Both proposed methodologies were tested in real-world cases, with the image background in each case to be characterized by non-uniform texture, i.e. the natural terrain is rugged at some locations, wooded land at some other or it is road that appears at the same hue as the aerial power lines.

In the result successful detection of the power lines before and after the discontinuity of the power line. The accuracy of the power line detection and the processing time are close to expectations. The proposed work offers a robust and low-cost way for the inspection of power transmission lines and so an effective way to detect the location where a cable fault has occurred.

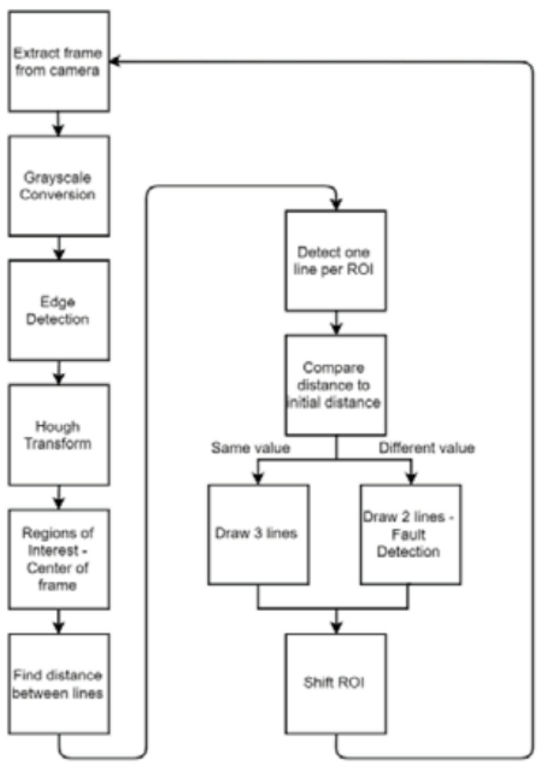


Fig. 6. Block Diagram of the power lines fault detection procedure using the Hough table values.

Paper 09

Image Acquisition of Power Line Transmission Towers Using UAV and Deep Learning Technique for Insulators Localization and Recognition.

This paper presents research results about autonomous inspection of power transmission towers and insulators using unmanned aerial vehicles (UAV). the proposed approaches for image acquisition of power line insulators

The process of acquiring the insulator image consists of following steps:

1. Acquire an image of an insulator and respectively calculate its center of gravity.
2. Control the quadrotor position in a way that the center of gravity of every insulator comes in the center of the image to be taken.
3. Correct the focus and zoom of the camera to acquire image with maximal possible resolution.

In this paper used methodologies areYOLO (You Only Look Once) system for detecting and recognizing the towers and the insulators. It is based on CNN and is using a single neural network for prediction. YOLO has simple construction and very good real-time performance for object detection. Compared to Fast R-CNN, YOLO has much higher detection accuracy and YOLO is “more than 1 000× faster than R-CNN.

The results show that the proposed scheme is applicable but there is a need to do some improvements concerning proper recognition in complicated backgrounds.

Paper 10

Research on Details Enhancement Method of UAV Inspection Image for Overhead Transmission Line.

In this paper they focused on the problem of poor processing effect of man-machine inspection image details. Purpose of this paper is a method for enhancing the details of aerial transmission line unmanned aerial vehicle inspection images.

By collecting and calculating the characteristic parameters of the UAV patrol image, the regional gray level and the optimal gain function value of the image are obtained. This paper is purely based on the principle of neural networks.

Results:

Multidimensional image data	File name	File size	After compression File size	Compression ratio
Image background test data	2#_w w1.0	158k	1068k	96.7%

Pixel test data	dat 02003.	23k	1085	68.9%
Dimension test data test data	0 dat 11& bh 12.0da t	247k	1098k	60.5%

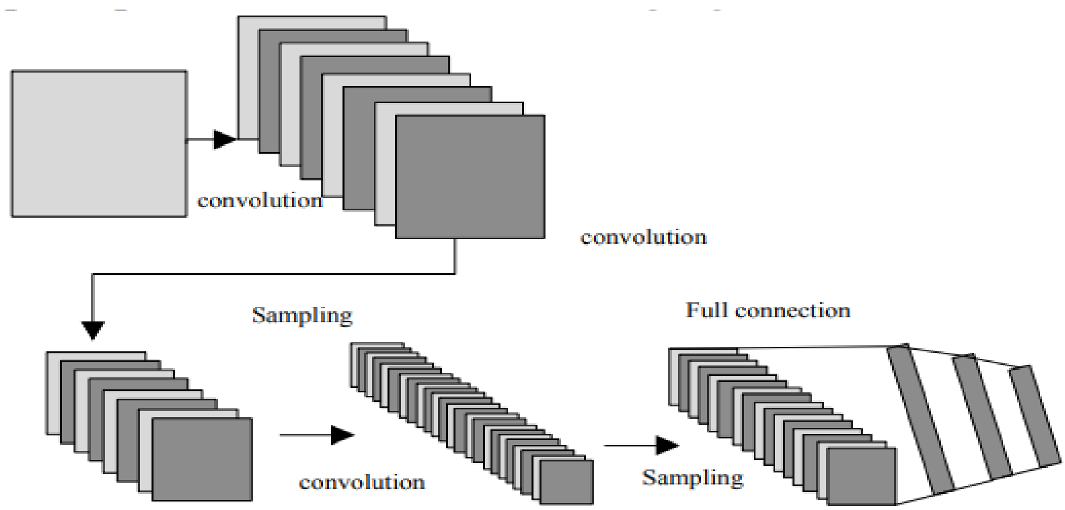


Fig. 1 principle of neural network information

Paper: 11

Detection of Power Line Insulator Defects Using Aerial Images Analyzed With Convolutional Neural Networks

This paper presents the automatic detection of insulator defects using aerial images, accurately localizing insulator defects appearing in input images captured from real inspection environments. Defect inspection is converted to a two-level object detection problem based on the cascading CNN. As the failure of power line insulators leads to the failure of power transmission systems, an insulator inspection system based on an aerial platform is widely used. Traditional methods, based on handcrafted features or shallow learning techniques, can only localize insulators and detect faults under specific detection conditions, such as when sufficient prior knowledge is available, with low background interference, at certain object scales, or under specific illumination conditions.

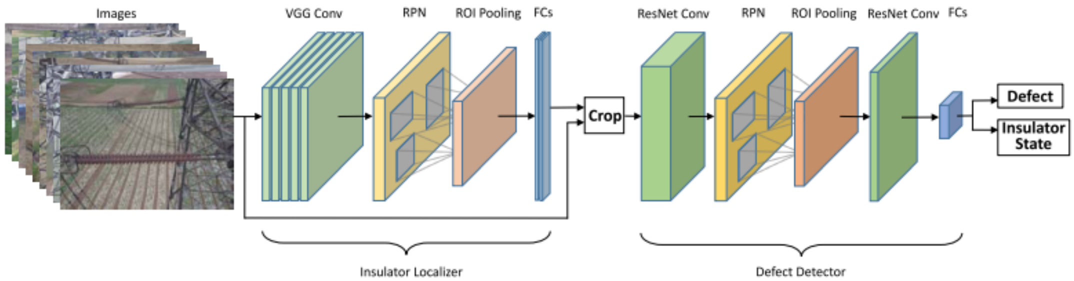


Fig. 4. Cascading insulator and defect detection architecture.

The cascading network uses a CNN based on a region proposal network to transform defect inspection into a two-level object detection problem. To defect images in a real inspection environment, a data augmentation method proposed four operations:

1. affine transformation
2. insulator segmentation and background fusion
3. Gaussian blur
4. brightness transformation.

PERFORMANCE OF DATA AUGMENTATION APPLIED TO OTHER METHODS

Model Name	Precision		Increased Precision
	Affine Transform	Our method	
ILN+ACF [25]	0.578	0.638	6%
ILN+CNN [16]	0.72	0.74	2%
Faster R-CNN [17]	0.767	0.795	2.83%

Defect detection precision and recall of the proposed method are 0.91 and 0.96 using a standard insulator dataset, and insulator defects under various conditions can be successfully detected. In results this method states the robustness and accuracy requirements for insulator defect detection.

Methodologies used:

Single shot multibox detector(SSD), YOLO, Generative adversarial nets(GAN), Support vector machine(SVM). Rectified linear units(ReLU).

Paper 12:

Recognition Method of Electrical Components Based on YOLO V3

This paper focused on detection and recognition of electrical components is an essential part of power inspection. To cure the main problems of traditional recognition methods of electrical components are low detection accuracy and poor real-time performance, this paper proposes a YOLO V3-based method for electrical component detection from UAV inspection images.

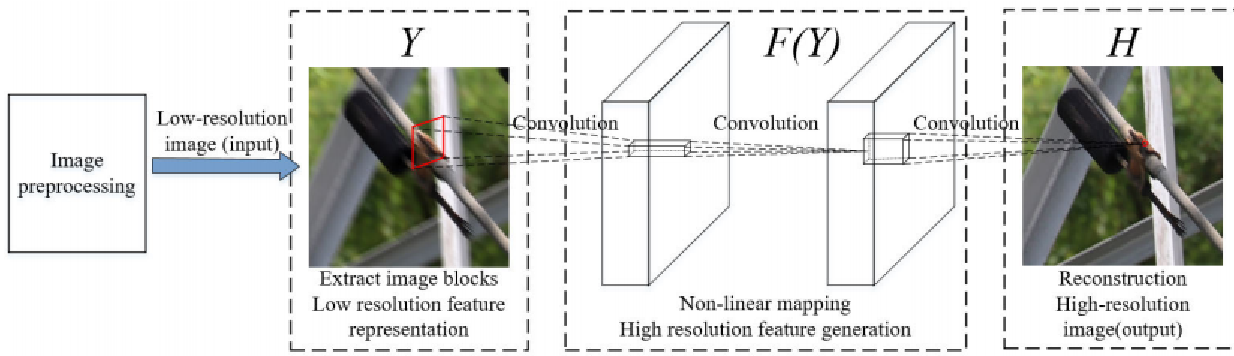


FIGURE 2. SRCNN network structure.

The YOLO V3 model, combined with SRCNN, can accurately identify the position and state of electrical components under different angles, backgrounds and illumination intensities. Super-Resolution Convolutional Neural Network (SRCNN) to realize super-resolution reconstruction on the blurred image, which achieves the expansion of the dataset.

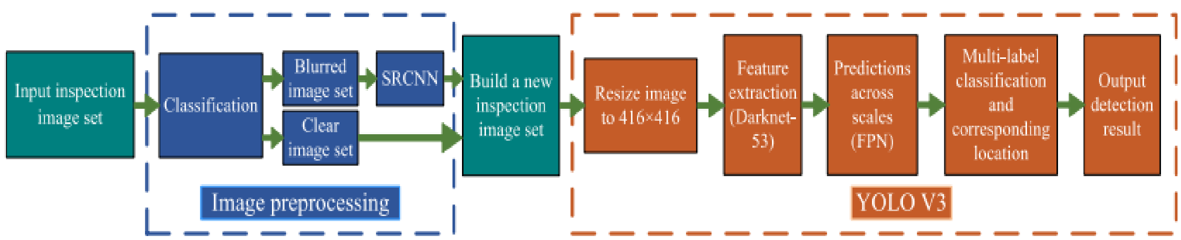


FIGURE 1. The main electrical components detection procedure.

The results of the experiment verify the effectiveness of the proposed method, and the technique reaches high recognition accuracy, good robustness, and strong real-time performance for UAV power inspection systems and the recognition accuracy of YOLO V3 is 1% to 3% higher than Faster R-CNN and SSD. Meanwhile, YOLO V3 outperforms the other two methods in recognition speed, which can achieve almost real-time performance

TABLE 1. The recognition accuracy of the three methods.

Algorithm	Training samples	Average Accuracy/% (400 iterations)	Average Accuracy/% (800 iterations)	Average Accuracy/% (1200 iterations)	Average Accuracy/% (1600 iterations)	Training time/h
Faster R-CNN	6432	66.16	77.26	86.35	92.14	25.21
SSD	6432	68.34	80.46	89.57	94.21	22.78
YOLO V3	6432	72.48	83.72	91.45	95.84	21.52

TABLE 2. Performance comparison of three algorithms.

Algorithm	Test samples	Test Accuracy/%	Test time/min	mAP
Faster R-CNN	1696	93.26	2.83	0.861
SSD	1696	95.33	1.57	0.913
YOLO V3	1696	96.45	1.13	0.936

Paper 13

Distribution Line Pole Detection and Counting Based on YOLO Using UAV Inspection Line Video

This paper proposes an innovative solution of pole detection and counting in the distribution network based on UAV inspection line video. Combined with the characteristics of YOLO's rapid detection, the convolution neural network is applied to the image detection of the pole state.

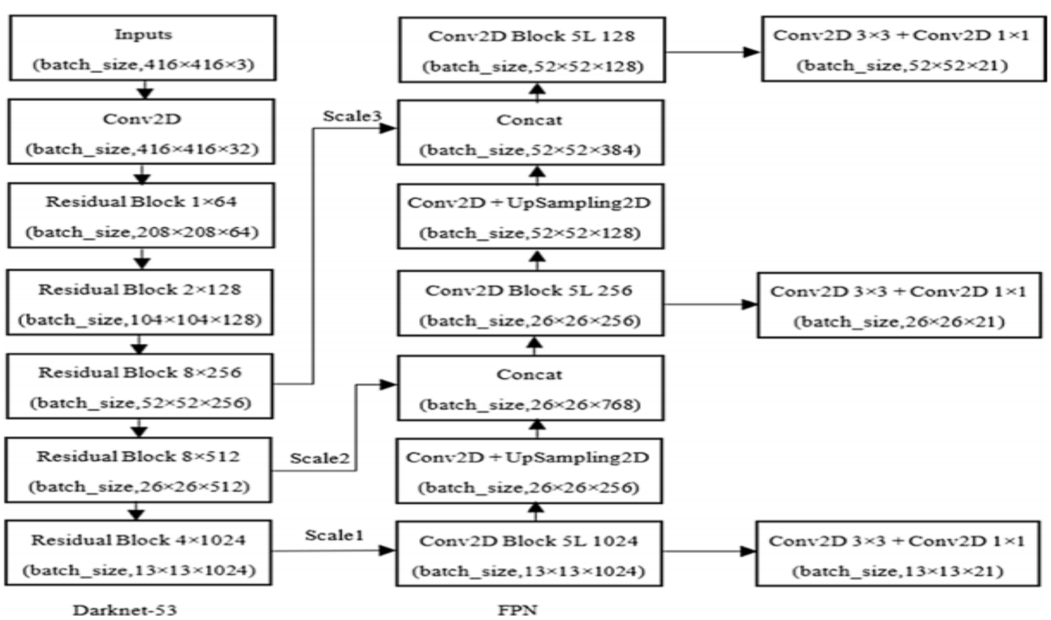


Fig. 1 Network structure of YOLO v3

This paper proposes the detection and counting algorithm of the distribution pole video from UAV based on neural networks. The neural network YOLO v3 model is used to solve the problem of detection and classification of distribution line poles. This model is mainly used to detect the distribution line poles in two states: upright pole and fallen pole. Firstly, in order to quickly determine the number of upright and fallen poles, the anchors of YOLO v3 are recalculated before applying the YOLO v3 training data set. Secondly, in order to accurately count the pole, ROI is set and a counting algorithm is presented. The anchor value is modified before image training by YOLO v3, and sets the corresponding ROI for the UAV inspection line standard. Compared with other algorithms, encouraging results are obtained. The detection precision of this algorithm is 90% which achieves the expected effect. This method can be applied to the rapid assessment of grid loss after a disaster.

The results show that the pole detection has better robustness, which indicates that this method can be extended to the rapid detection of the transmission line tower and distribution line pole in various environments if appropriate training data sets are available.

Journal of Electrical Engineering & Technology

Table 2 The results of 6 models in the dataset ($t=0.25$)

Model	Precision	Recall	F1-score	mAP (%)	Upright pole ap (%)	Fallen pole ap (%)
YOLOv3 288×288	0.89	0.91	0.90	89.90	89.71	90.09
YOLOv3 352×352	**0.90**	**0.92**	**0.91**	**90.45**	**90.09**	**90.81**
YOLOv3 416×416	**0.90**	**0.92**	**0.91**	90.36	89.92	**90.81**
YOLOv3 480×480	**0.90**	0.91	0.90	90.23	89.71	90.74
YOLOv3 544×544	0.88	0.89	0.89	89.99	89.21	90.77
Faster RCNN	0.75	0.67	0.71	71.99	60.74	83.24

Paper 14

MTI-YOLO: A Light-Weight and Real-Time Deep Neural Network for Insulator Detection in Complex Aerial Images

In this paper, focused on detection of insulators in complex aerial images with a deep neural network (MTI-YOLO). For that firstly, insulator images captured by a UAV were collected and a composite insulator dataset “CCIN_detection” was constructed, which contains more common aerial scenes than that of the “CPLID” dataset. After that, to improve the accuracy and robustness of different-sized insulator detection, three improvements were implemented in the MTI-YOLO network. Finally, the proposed MTI-YOLO network and the compared networks were trained and tested on the “CCIN_detection” dataset.

Results and analysis show that the proposed network achieves better performance than some YOLO networks. Specifically, compared with the network of YOLO-tiny, the AP value of our proposed network is 17% higher, and the precision is 16% higher. Compared with the network of YOLO-v2, the AP value of our proposed network is 9% higher, the precision is 21% higher, the memory usage is 25.6% lower, and the FLOPs are 10% lower.

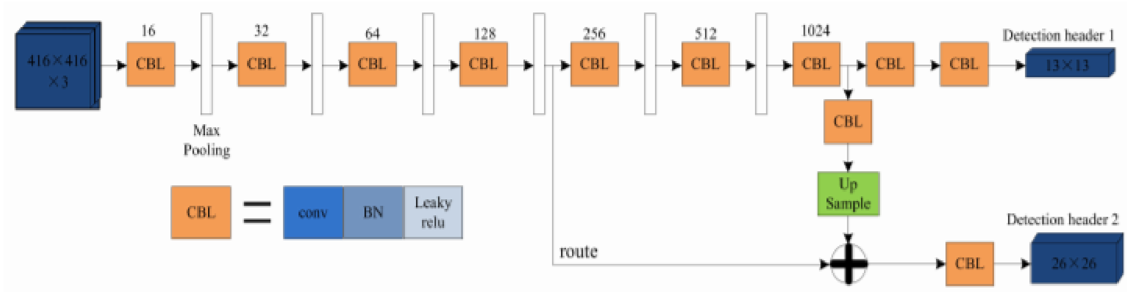


Figure 2. The network structure of You Only Look Once (YOLO)-tiny.

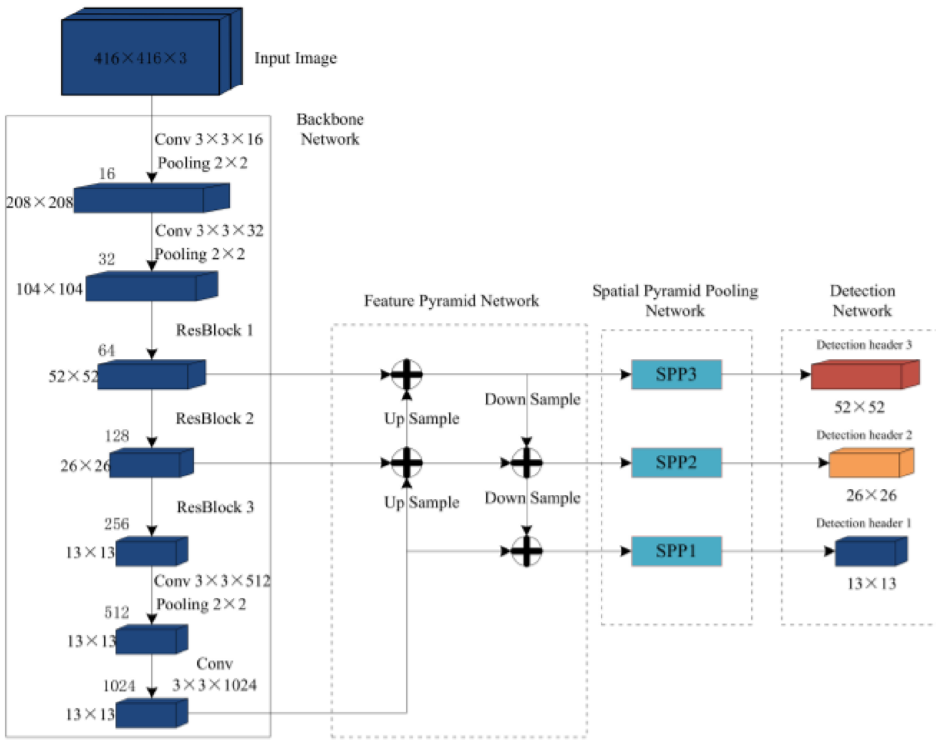


Figure 3. The entire structure of the modified YOLO-tiny for insulator (MTI-YOLO) network.

Compared with the network of YOLO-v3, the AP value of our proposed The network is just a little lower, the precision is 1% higher, the memory usage is 38.9% lower, the FLOPs are 59.6% lower, and the running time is far less than that of YOLO-v3. Therefore, It can be concluded that using the proposed network to detect insulators can achieve good performance and it has the potential to be deployed on embedded devices.

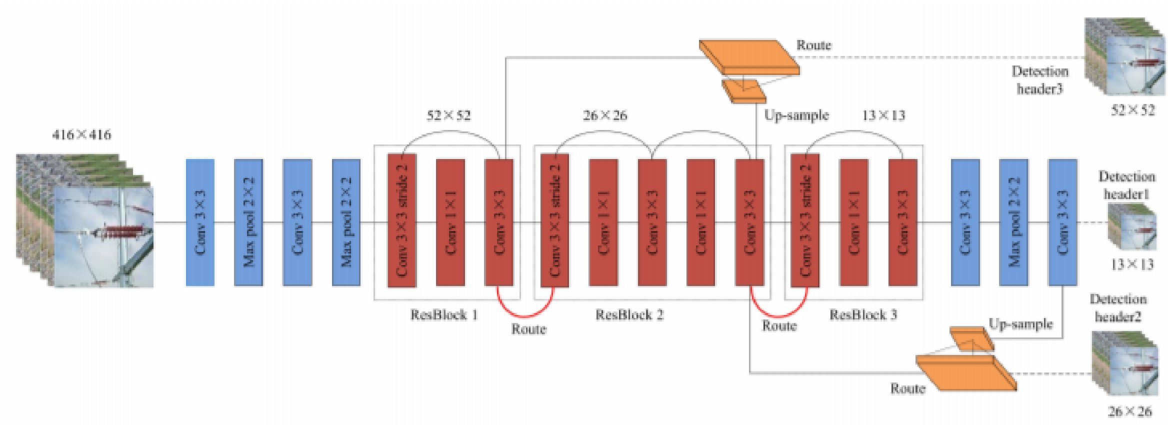


Figure 4. The structure of backbone network.

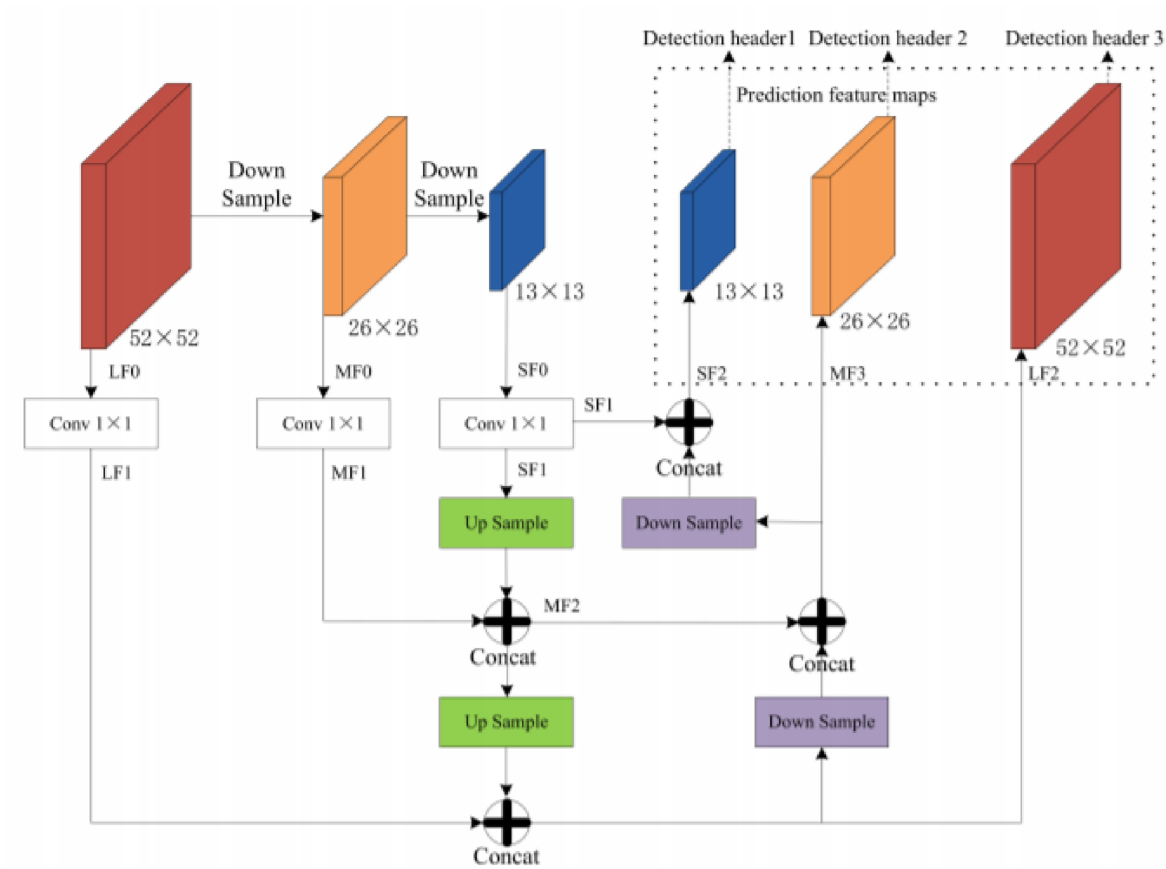


Figure 6. The structure of multi-scale feature fusing.

Paper 15

IN-YOLO: Real-time Detection of Outdoor High Voltage Insulators using UAV Imaging

This paper focused on detection of Insulators from aerial images is the first step towards performing real-time classification of insulator conditions using Unmanned Aerial Vehicle. Model proposed cost-effective solution for detecting insulators under the conditions of an uncluttered background, varied object resolution and illumination conditions using You Only Look Once (YOLO) deep learning neural network model from aerial images insulator detection followed by condition classification on insulators with clean, water, snow, and salt surfaces.

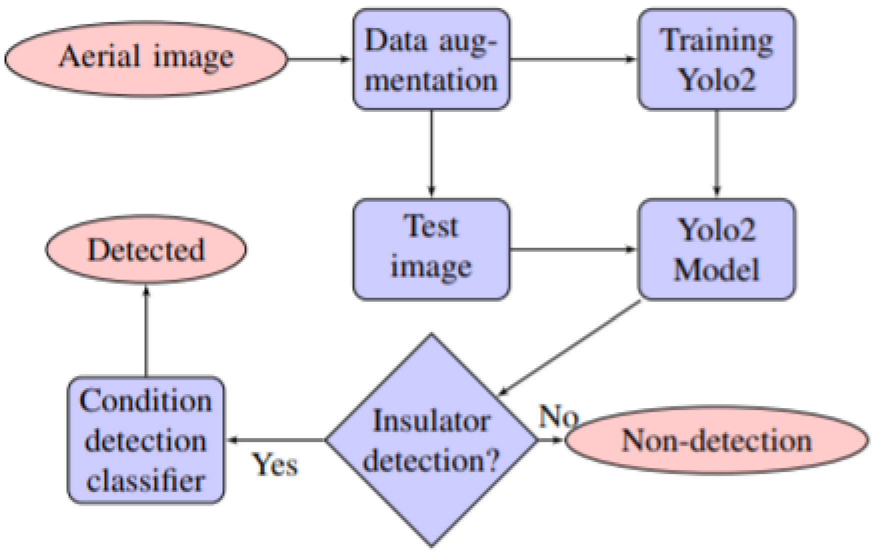


Fig. 2: Overall flow chart of insulator detection and surface condition classification from aerial images.

The data augmentation to avoid overfitting with a training set size of 56000 image samples. It is demonstrated experimentally that this method can accurately locate the insulator on UAV based real-time image data. This can be extended for real-time multi-class detection, including towers, poles, and power lines detection.

Result shows the ability of real-time prediction using UAV video shooting with a high enough accuracy of 88%.

TABLE I: Classification accuracy on four insulator conditions, i.e. Clean,Water, Snow, and Ice

Classifier	Accuracy (%)	Classifier	Accuracy (%)
CNN	87 ($\pm$9.3)	Bayes net	86 ($\pm$4.5)
SVM	80 ($\pm$1.1)	Random forest	87 ($\pm$5.1)
NN	40 ($\pm$4.1)	AdaBoost.M1	82 ($\pm$4.2)

Paper 16:

Data analysis in visual power line inspection: An in-depth review of deep learning for component detection and fault diagnosis.

This paper focused on comprehensive review of data analysis for visual power line inspection. The latest developments have been summarized and the key characteristics of these studies have been discussed.The widespread popularity of unmanned aerial vehicles enables an immense amount of power line inspection data to be collected. It is an urgent issue to employ massive data, especially the visible images to maintain the reliability, safety, and sustainability of power transmission.

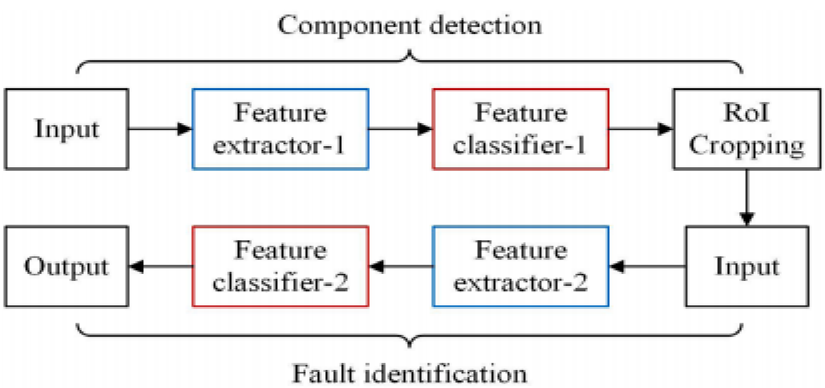


Fig. 7. The common procedure of fault diagnosis.

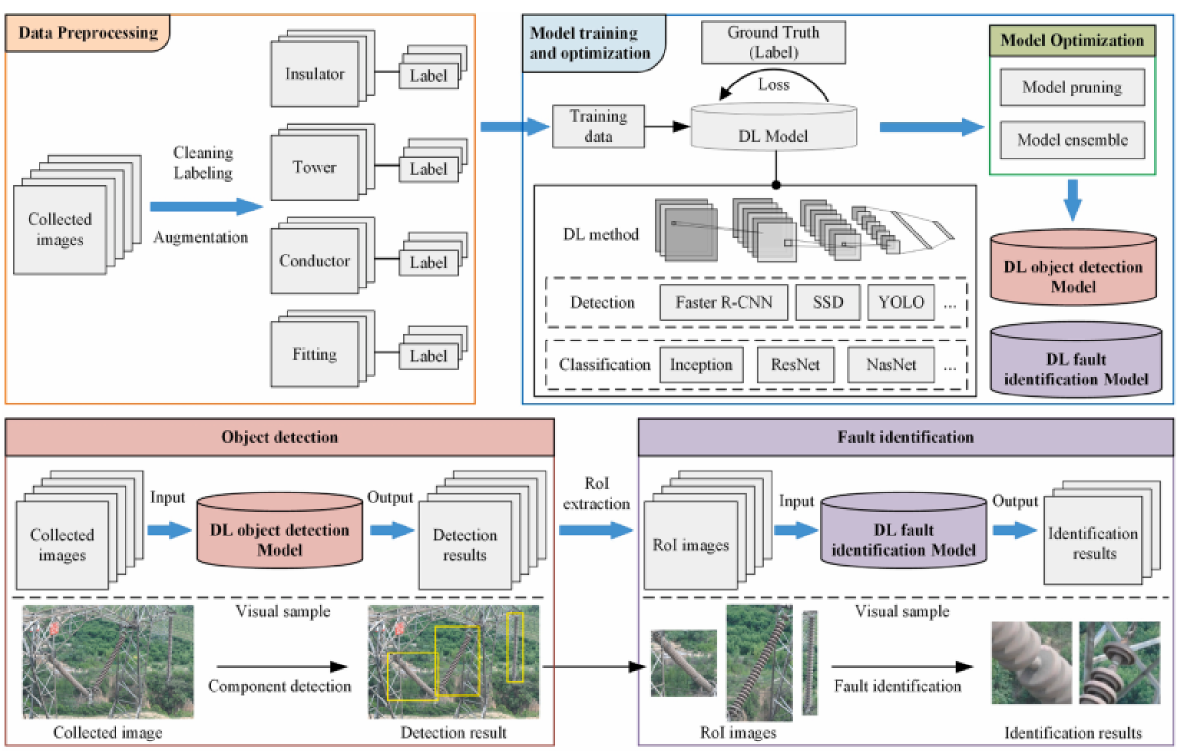


Fig. 13. A solution of data analysis system for power line inspection based on deep learning.

Summary of the literature on deep-learning-based approaches for the inspection of power line components.

Characteristic	Inspection item	Method	Data size	Pixel size	Core idea
Direct utilization of existing frameworks	Missing-cap of insulator	Faster R-CNN (Liu et al., 2018c)	4500	500 × 500	Utilize Faster R-CNN to detect insulator and it's fault
	Tower detection	Faster R-CNN (Bian et al., 2019)	1300	640 × 480	Utilize Faster R-CNN to detect tower
	Conductor detection	FCNs (Hui et al., 2018)	600	1280 × 720	Utilize FCNs to detect power line
	Fitting detection	Faster R-CNN (Wang et al., 2017c)	6000	500 × 500	Utilize Faster R-CNN to detect fittings
	Insulator detection	YOLO (Wang et al., 2018)	1000	448 × 448	Utilize YOLO to detect insulator
	Tower detection	YOLOv3 (Chen & Miao, 2019)	13,429	352 × 352	Utilize YOLO to detect tower
	Insulator detection	SSD (Xu et al., 2018)	2500	512 × 512	Utilize SSD to detect insulator
	Conductor detection	cGAN (Chang et al., 2018a)	5500	256 × 256	Utilize cGAN to detect conductor
	Insulator detection	cGAN (Chang et al., 2018c)	3000	256 × 256	Utilize cGAN to detect insulator
Extracting deep features	Surface-fault of insulator	M-PDF (Zhao et al., 2016b)	1000	227 × 227	Extract features by CNN in multi image patches
	Corrosion of tower	CMDELM-LRF (Maeda et al., 2018)	3017	50 × 50	Extract features by CNN in image and text
	Missing-cap of insulator	DCNN (Yang et al., 2019)	2951	256 × 256	Extract features by CNN in sub-windows of aerial image
Network cascading	Missing-cap of insulator	Faster R-CNN + U-net(Ling et al., 2018)	620	1024 × 1024	Utilize Faster R-CNN to detect insulator and U-net to detect the fault
	Missing-cap of insulator	Faster R-CNN + FCN (Gao et al., 2017)	3650	1215 × 1048	Utilize Faster R-CNN to detect insulator and FCN to filter out background
	Missing-cap of insulator	ILN + DDN (Tao et al., 2020)	1956	—	Propose an Insulator localizer network and a Defect detector network
Objective to solve data insufficiency	Insulator detection	Synthetic method + cGAN (Chang et al., 2018b)	265	512 × 512	Propose a synthetic method to synthesize training samples
	Missing-cap of insulator	PPM (Tian et al., 2018)	—	—	Introduce a preprocessed parallel method by data augmentation
	Surface fault of insulator	SPPNet-TL (Bai et al., 2018)	278	227 × 227	Training on a small dataset based on transfer learning
	Insulator detection	SSD + TS-FT (Miao et al., 2019)	8005	300 × 300	Introduce a two-stage fine-tune strategy for training on the small dataset
	Conductor detection	WSL-CNN (Lee et al., 2017)	8400	512 × 512	Apply weakly surprised learning to train the conductor detection model
Improving by domain knowledge	Missing-cap of insulator	EL-MLP (Jiang et al., 2019)	485	300 × 300	Aggregate deep learning models in perception levels based on ensemble learning
	Missing-cap of insulator	SO-FCN (Chen et al., 2019a)	300	400 × 600	Introduce a mathematical morphology operation to optimize the detection procedure
	Missing-cap of insulator	Up-Net + CNN (Sampedro et al., 2019)	2800	256 × 256	Propose a diagnosis strategy for missing-cap detection based on semantic segmentation
	External force damage	Modified Faster R-CNN (Xiang et al., 2018)	2199	600 × 1000	Improve Faster R-CNN to detect engineering vehicles based on their characteristics

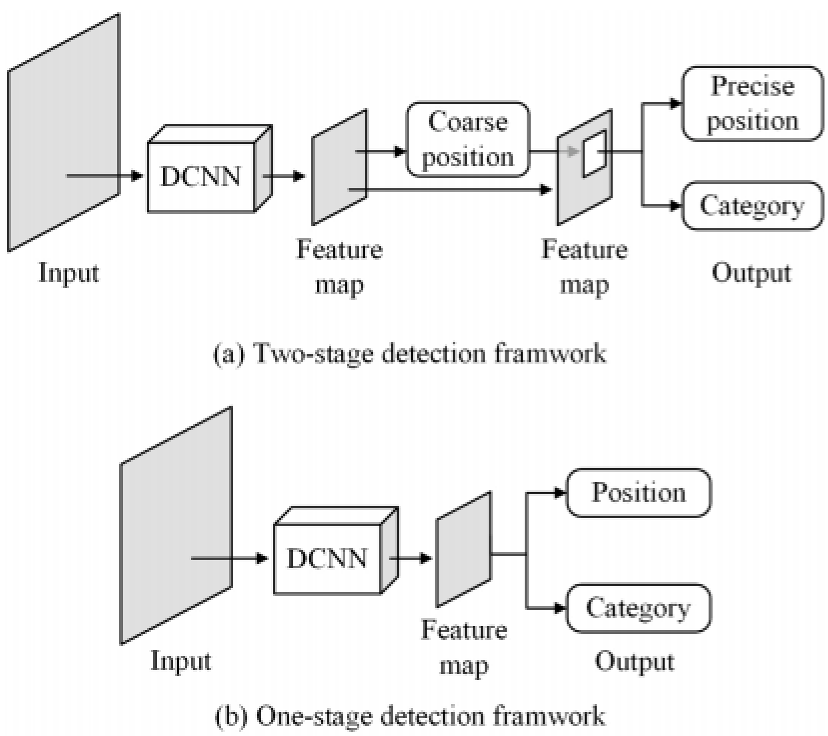


Fig. 10. The diagram of (a) two-stage and (b) one-stage detection framework based on deep learning.

Firstly, studies in power line component detection in inspection images are reviewed from the perspective of different image features including color, shape, texture, fusion, and deep features. Then, the literature survey of power line fault diagnosis is conducted in a fault specific way including surface fault of insulator, missing-cap of insulator, tower corrosion, bird's nest, fallen tower, broken strand, foreign body, vegetation encroachment, broken fitting, and missing-pin of fitting.

Next, an in-depth summary of deep-learning-based works in the area of data analysis of power line inspection is introduced. These articles are categorized into frameworks, deep feature extraction, network cascading, data insufficiency issues, and improvement based on domain knowledge. Further, a solution of data analysis system for power line inspection which is mainly based on deep learning is proposed. This system consists of four parts: data preprocessing, component detection, fault identification, and model training and optimization.

Paper 17

Vision-based autonomous navigation approach for unmanned aerial vehicle transmission-line inspection.

In this paper proposed a safe and robust transmission tower-based autonomous navigation approach for UAV transmission-line inspection. Specifically, to achieve the real-time and robust localization of a tower, a detection-tracking visual strategy that integrates the detection and tracking is used. Here apply faster R-CNN to the detection-tracking framework for a trade-off between speed, precision rate, and recall. At the stage of flight heading calculation, FCNs are first employed to realize the transmission-line extraction of great importance, which is effective, even in more complex environments. segmentation by fully convolutional networks is applied to the extraction of transmission lines, from which the vanishing point (VP), an important basis for determining the flight heading, can be obtained. For more robust navigation, the designed scheme addresses the scenario of a nonexistent VP. With respect to the precise flight defined by VP, the algorithm based on the RANSAC strategy, together with linear and nonlinear optimization, is employed. Additionally, an experimental flight heading is adopted to cope with the case in which a VP is nonexistent. Finally, with the newly designed experimental platform, continuous flight experiments without GPS demonstrated the effectiveness of the navigation model and proposed methods.

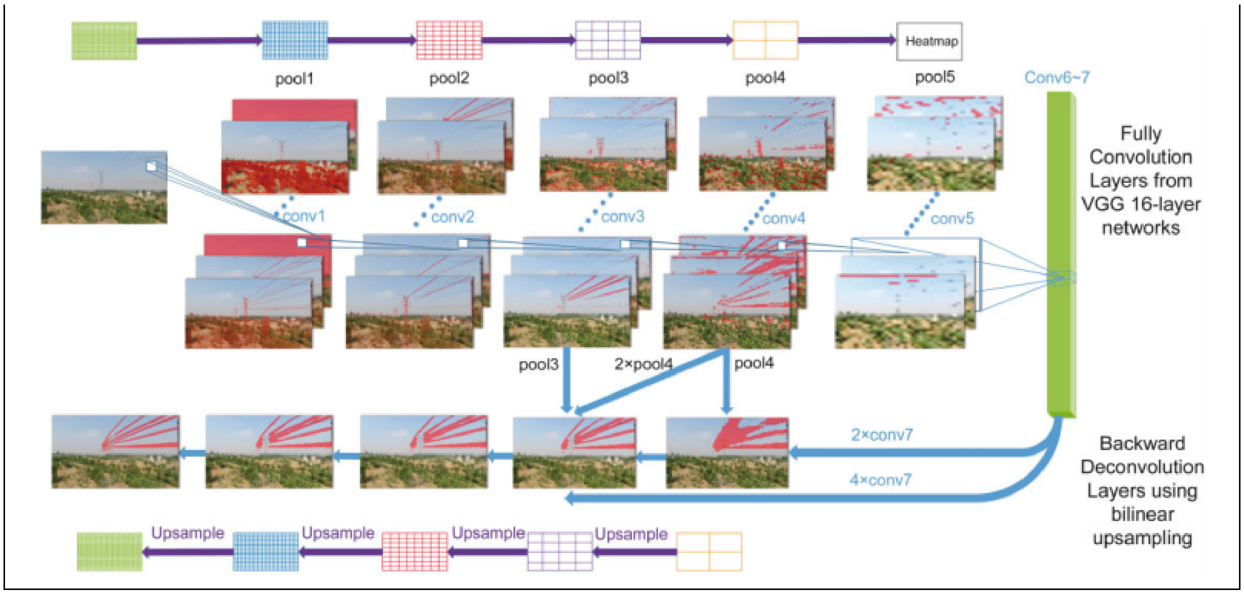


Figure 6. Structure of FCNs and feature maps for transmission-line segmentation. FCNs: fully convolutional networks.

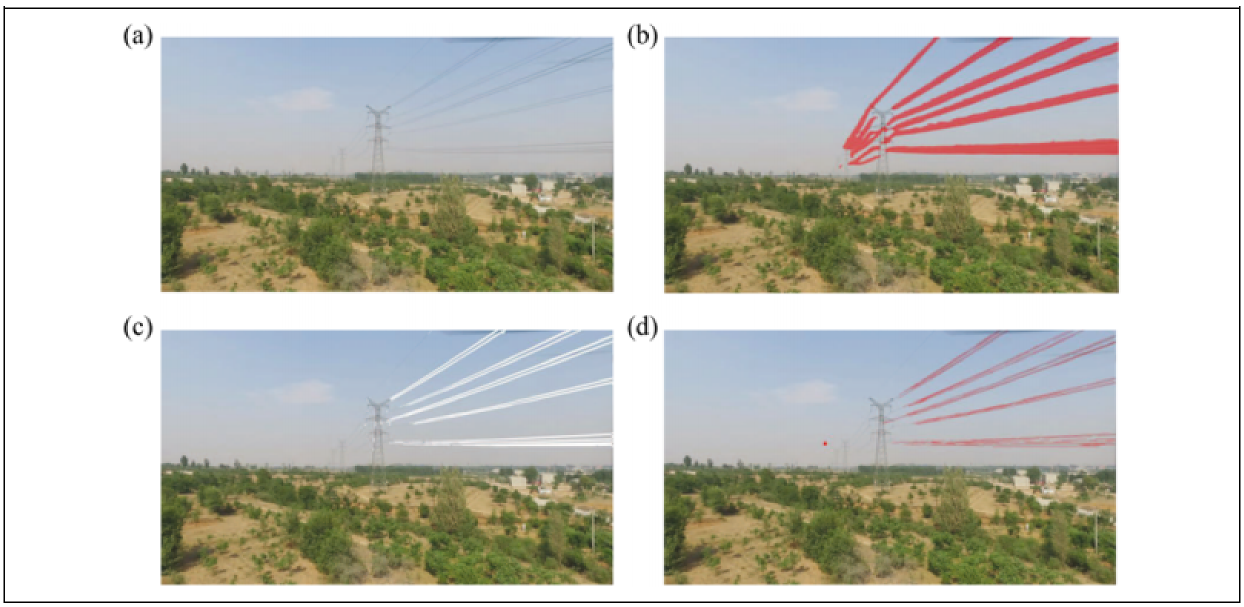


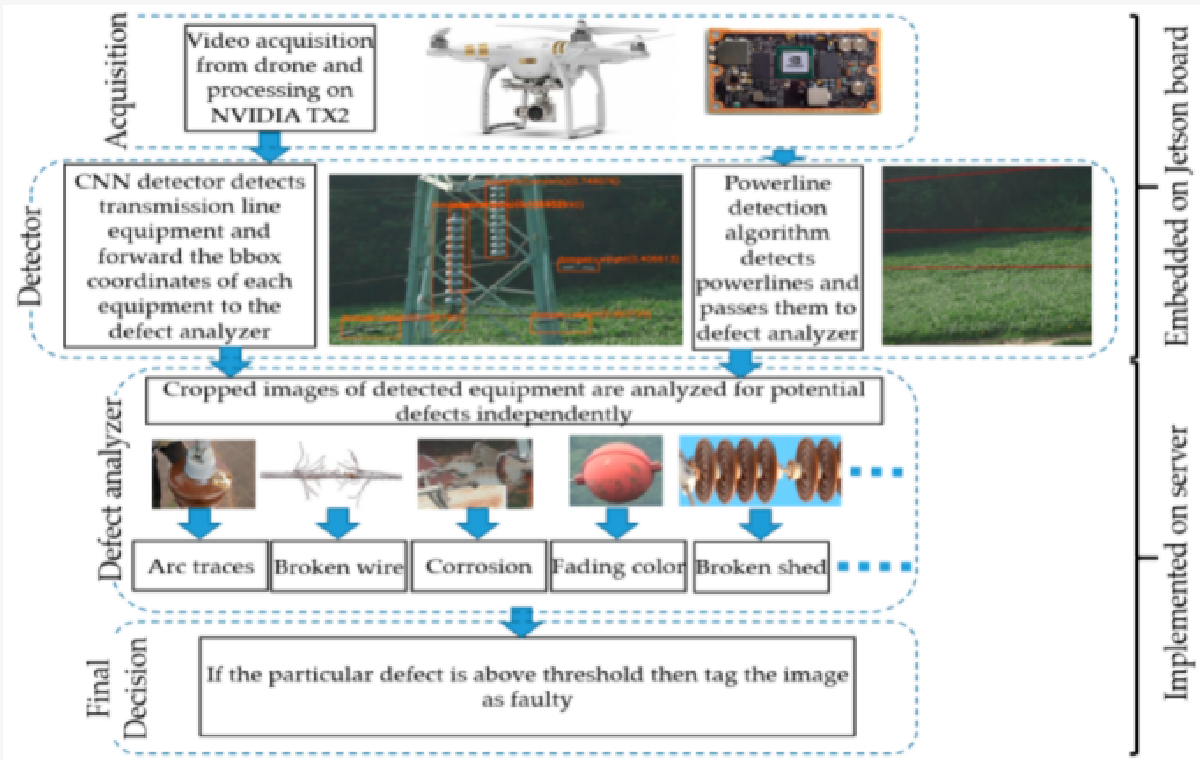
Figure 7. Process of proposed VP detection. VP: vanishing point.

Paper 18

A Drone Based Transmission Line Components Inspection System with Deep Learning Technique

In this paper, an automatic transmission line components detection and defect detection system is proposed.The detection performance of the modified YOLO V3 approach is shown to outperform the performance of the baseline model. The system can also detect electrical power lines using the proposed power line detection algorithm. The proposed power line algorithm shows dominant performance on the given dataset as compared with the LSD and EDlines methods, both in terms of speed and accuracy. Once the power line components are detected, a defect detection system checks for potential defects. The performance of the proposed defect detectors suggests that handcrafted approaches can be used to detect some of the types of defects in situations where the availability of a large number of defected samples is not viable. The proposed system is tested on a large, unbiased, unconstrained evaluation dataset of transmission line components images.

Figure 2. Overall system diagram.



The proposed automatic inspection system provides practical solutions to meet the major requirements of the modern electric transmission system. The feasibility of using a drone along with a robust real-time CNN-based object detector can eliminate the danger associated with the duties of electrical workers (physically climb transmission towers on a regular basis) or use of expensive patrolling helicopters to inspect the conditions of transmission line components. The proposed defect analyzer system can also help in reducing the time to identify the faulty components. The proposed balisor fading defect detector has a 100% recall rate which means it does not miss any faulty components, while the 76% precision rate means that only 24% of the detection can be a false alarm. Hence, even if the second round of inspection is required, the proposed inspection system can save up to 76% of the manual inspection work. Overall, the proposed inspection system not only offers ease of implementation and scalability but also gives an economical advantage over the manual inspection counterpart.

Results show that the proposed detection and localization system is robust against a highly cluttered environment, while the proposed defect analyzer outperforms similar research in terms of defect detection precision and recall. With the help of the proposed system automatic defect analyzing system, manual inspection time can be reduced.