Power Line Detection for Aerial Navigation Using Deep Learning

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Abstract. Power line detection is crucial for ensuring the safety of low-altitude aircraft such as uncrewed aerial vehicles and helicopters. Although many traditional techniques have been used for this task, their detection accuracy has often been limited. To address this issue, we propose a deep learning–based approach for power line detection that demonstrates strong performance on both visible-spectrum and infrared images, achieving detection accuracies of 91.75% and 99.12%, respectively. The proposed method effectively identifies power lines across varying environmental conditions and complex backgrounds. Its stable performance over a wide range of experimental settings highlights the robustness of the approach. In addition, the superior effectiveness of infrared imagery compared to visible-band images, as observed in this study, is particularly noteworthy.

1 Introduction

Power lines are crucial part of the electrical grid, enabling the transfer of electrical energy over long distances. Power line detection (PLD) refers to the method used to locate and identify electrical lines, often using various technologies and methods, to prevent accidents, enhance safety, and support maintenance and inspection activities. This detection is essential for various applications, including construction, aerial navigation, and the operation of autonomous vehicles and drones. PLD plays a significant role in many fields, such as the military, aviation, Uncrewed Aerial Vehicle (UAV) and helicopter safety. If a helicopter or drone touches a power line, it may cause fatalities for both the aircraft and the powerhouse. The electrical line may be disconnected, and the power supply may be interrupted. It may take long time to resolve the damages.

Additionally, there are chances of losing soldiers, drivers and passengers of aerial vehicles. More often than not, US forces reported losing their UAVs or helicopters

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to electrical power wires rather than enemies. Power lines are usually skinny, and therefore not easily visible in most backgrounds. Moreover, unfavorable atmospheric conditions like smog, cloud bursts, dust, etc. may further reduce power line visibility. On the other hand, humans have poor night vision compared to other animals, like cats and owls, because the objects cannot form on the retina in insufficient light. Unlike visible band imaging, infrared imaging enables us to see-through in the dark. In this regard, Yang et al. [1] have published a comprehensive review article that explores various state-of-the-art techniques in power line inspection, offering valuable insights for researchers working in the field of smart grids. The article begins with an overview of different deep learning models and traditional pattern classifiers, which are used for detecting power-line components, including power lines, power towers, and defects. It also provides an insightful discussion on the use of various platforms, such as automatic climbing robots, UAVs, and helicopters, while highlighting their limitations in the context of power line inspection. Additionally, the article reviews and analyzes the different sensory systems employed in power line inspection. In conclusion, it offers a detailed review of existing methods for power line detection, providing a thorough analysis aimed at general readers.

With the advancement of deep networks and their ability to automatically extract features, deep Convolutional Neural Networks (DCNNs) have emerged as the backbone architecture for most object detection frameworks till date[2], [3] [4], [5]. Hence, CNN is undoubtedly the front-runner for power-line detection from UAV and other kind of aerial images. Gao et al.[6] have developed a modified cGAN model, which outperforms other state-of-the-art models, such as the Fully Convolutional Network (FCN), UNet [7], Pix2pix[8], and other approaches, in terms of accuracy. However, the performance of DCNNs is heavily dependent on large amounts of training data, and annotating this data is a time-consuming task.

With the rising improvement of Artificial intelligence (AI) strategy, a few scientists have attempted to lead PLD issues with AI. While considering AI to settle PLD issues, one can direct it in two ways. The first is forming the PLD [9] issue as a parallel grouping task, for example, to decide whether the scene contains power lines. Currently, most works follow this approach [10] [11]. In light of AI, the PLD strategy comprises a few phases. Right off the bat, one necessity is pre-handling for pictures, such as resizing images and eliminating commotion. Then, highlights ought to be separated and chosen appropriately. At long last, the highlights are taken care of into classifiers to do characterization. Sample images of the PLD dataset, VL images, and IR images (including Power Line and excluding Power Line) are shown in Fig. 1. Therefore, the main contributions of the current study is mentioned below in a nutshell.

- A robust and highly effective CNN-based framework is designed for power-line detection. The framework is capable of handling the complexities inherent in both visible band and infrared images, addressing the challenges posed by variations in lighting, noise, and environmental conditions across these imaging modalities.
- To validate the framework's effectiveness, extensive experiments have been conducted, fine-tune network parameters for optimal performance. The results demonstrates that developed method consistently outperforms state-of-the-art methods on both visible and infrared image datasets.

The remaining portion of the paperwork has been organized as follows: A thorough assessment of relevant studies is given in Section 2. The suggested technique is presented in Section 3. The experimental results and a perceptive analysis of the empirical data are presented in Section 4. The work is finally concluded and future research possibilities are outlined in Section 5.

2 Related Works

In this section some previous research works have been discussed which can motivate our experiment as follows: Raghatate et al. [12] have described the various night vision techniques and divided them into three categories, i.e, Image intensification, Active illumination, and Thermal imaging, Unmanned aerial Vehicles also known as UAV are becoming a widespread and an essential tool for various activities ranging from military usage to simple day-to-day applications, such as infrastructure inspection, camera-based sensing, aerial imaging etc. Koppány Máthé and Lucian [13] have reported some survey vision and control methods that can be applied to low-cost UAVs, and they further lay out some inexpensive, well-known platforms and domains of application where they are useful. Alam et al. [14] have proposed an effective way of detecting Power Line Faults and communications. This method introduces an exciter,electromagnetic surface waves (EM waves) on unshielded power line cables by means of a new conformal surface wave (CSW). The method is more straightforward and cost-effective as the exciter conformal surface wave (CSW) is affordable, minor, and easy to place on a power cable. Liu et al. [15] have presented a faster power line detection and localization algorithm and also proposed a guidance architecture for active vision-based UAV (Unmanned Aerial Vehicle) guidance. A line-fitting method is utilized to refine the potential power lines in the collected images after steerable filters are employed to detect ridges in the detection stage. In Table 1 some recent deep-learning driven methods for It clarifies how to inspect and detect faults in electricity lines.

Zhang et al. [23] have applied deep learning techniques to the power line detection problem. The main takeaway from the proposed method is that a Convolutional Neural Network (CNN) is employed. The problem is treated as a binary classification problem, containing two classes - either the image consists of a power line or not. The network structure of the deep learning framework is very similar to that of the famous VGG-16 network [24][25], which contains 13 convolutional layers, five pooling layers, and three fully-connected layers. The weights and the bias in the network are trained and optimized by using labeled training images. The input image used is resized to 224×224 so that the deep learning model can process it. The experimental results outperform conventional machine learning-based methods, as the study demonstrates. 95% of the photos with power lines are successfully recognized by the suggested deep learning technique. Seikh et al. [26] have proposed a HOG feature-based recognition for VL and IR images. The experimental results on IR images are 94.00%, and for VL images, 83.40%. Lu et al. [27] have proposed a line-tracking algorithm [28] [29] suitable for power line inspection based on unmanned aerial vehicle (UAV) [30]. According to their work, the proposed algorithm boasts the advantage of small computation and fast calculation speed. Even during high-speed flight, the proposed algorithm can shoot the angles of a visible-light camera, infrared thermal imager (IR), and ultraviolet imager (UV); the airborne inspection system is always aimed at the power line, the quality of videos and images are ensured, and thus improving the overall efficiency and practicality of the UAV-based power line inspection system [31] and the performance of the system are further enhanced.

Table 1: Overview of different deep-learning based methods for power-line inspection methods in a nutshell

Method	Baseline Network	Dataset	Remarks
Gao et al.[16]	GAN	• In-house UAV dataset • Captured using drone in-built camera	• Patch based power-line insulator segmentation network is designed • High accuracy in noisy images
Jiang et al.[17]	SSD	• China power grid UAV images • Images contain at least one insulator and one fault object	• Network trained using multi-level training modalities • High accuracy in detecting insulator fault in complex scene images • High precision due to ensemble approach
Li et al.[18]	YOLOv3 + DarkNet53	• Birds nest dataset • Acquired using UAV flights and internet	• Designed for high voltage power-line inspection • Provides an autonomous flight control system
Lv et al.[19]	Cascaded RNN	MS-COCO 2017[20]	• Bi-linear interpolation and feature enhancement strategy • Mini-batch K-means clustering • Detect 10 types of obstacles
Wang et al.[21]	Improved YOLOv5	China power-line insulator dataset [22] + NID dataset	• K-means clustering for accurate anchor-box fitting • Recursive gated convolution layer for intrinsic feature extraction • Misclassification and false positive in low-lighting effect

3 Proposed Methodology

In this paper, a deep learning driven method has been developed to detect power lines with the help of image processing and machine learning. A CNN architecture is applied as baseline network rather than using other PLD methods to obtain higher accuracy in power-line detection from complex images. All experiments are done on the PLD dataset and, using the detection of power-lines, are recognized by CNN. The description of power line images in the visible band and infrared imaging of power lines is defined in Sections 3.1 and 3.2, respectively, and the architecture of CNN with parameters used for this experiment is described in Section 3.3.

3.1 Power Line Imaging in Visible Band

The sun, lights, candles, and fire are everything that individuals naturally consider concerning light; however, noticeable light comes from many sources and tones. Several wellsprings of noticeable light include TV and PC screens, gleam sticks, and firecrackers. The apparent light range is the fragment of the electromagnetic range that the natural eye can see. All the more basically, this scope of frequencies is called noticeable light. Commonly, the natural eye can identify frequencies from 380 to 700 nanometres. VL band images are shown in Fig. 1

Figure 1: Samples of power line imaging in visible band (a) with power lines and (b) without power lines.[32]

3.2 Infrared Imaging of Power Lines

IR imaging began with mechanical filtering frameworks, in which single-component identifiers or little arrangements of straight clusters cover the entire field of view by moving the view in X and Y bearings. Such frameworks required IR locators to have a high responsibility and a quick reaction speed. Thus, warm IR identifiers didn't find their place in mechanical examining IR imaging frameworks. IR imaging innovation is utilized to gauge the temperature of an item. IR images are shown in Fig. 2

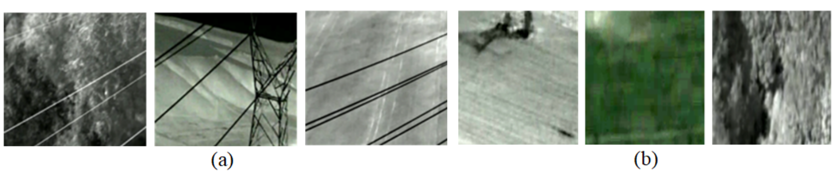

Figure 2: Sample infrared images (a) with power lines and (b) without power lines

3.3 Architecture of the applied CNN Model

A CNN architecture-based model is used to detect power lines. This architecture is applied on the PLD dataset [24]. This section describes the experimental parameters used in the CNN model with a model summary. The power line detection problem experiment was treated as a two-class classification problem known as a binary classification problem. The two classes of the given problem are: (a) The power line exists in the image. (b) The power line does not exist in the image. This method can also be applied in the real world by activating an alarm whenever a power line is detected or is near the flying vehicle. For automatic power line detection, we have to train the CNN model first with the dataset sampling two types of images with power line (positive training data) and without power line (harmful training data) and produce the output of '1' with power line, '0' for without power line. The dimension of VL and IR images 128 $\times$ 128 pixels. Configuration of applied CNN model and parameters are shown in Table 2, besides, the detailed layer-wise architecture of employed CNN and corresponding number of trainable and non-trainable parameters are shown in Fig. 3 and Fig. 4, respectively.

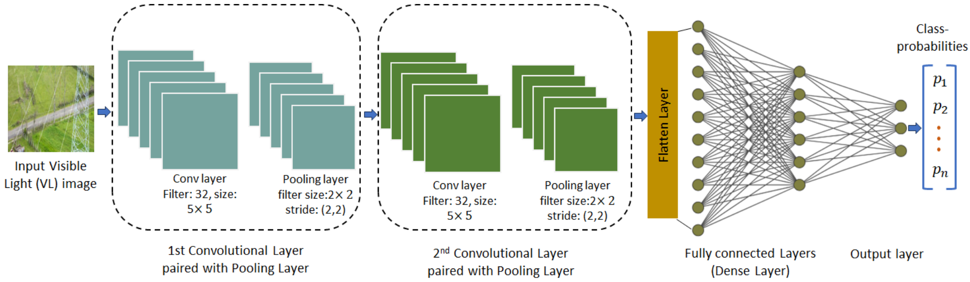

Figure 3: Layer-wise network architecture of employed CNN

Table 2: List of hyper-parameters and their assigned values of the applied CNN model.

Parameter	**Value**
Epoch	100 / 50
Batch Size	500
Learning Rate	0.001
Number of Train Image	3200
Learning rate	0.001
Loss-function	Categorical cross-entropy

4 Experimental Findings and Analysis

Experiments have been carried out on a composite power-line dataset containing two subsets, i.e., (i) Visual light power line images, and (ii) Infrared power line images. CNN is applied on both image sets separately. The overview of the PLD dataset is shown in Table 3. Experimental results on VL images and results on IR images are shown in Section 4.1 and Section 4.2 respectively. This dataset was originally developed and released by Yetgin et al. [32]. It contains 4000 VL images and 4000 IR images of dimension 128x128 pixels, and each set includes 2000 shots with electrical cables and 2000 shots without electrical wires.

Table 3: Class-wise image distribution of the power-line detection dataset [32].

Image Type	Total number of images	Power Line (Included)	Power Line (Excluded)
IR Images	4000	2000	2000
VL Images	4000	2000	2000

4.1 Detection Performance in VL Band

In these experiments, different configurations have been considered, such as gray/color version of the VL images, different epochs, different batch size etc. Detail parameter-wise results have been shown in Table 4. The best accuracy i.e. 91.75% is obtained with the original VL images with 100 epochs, 500 batch size, and 8:2 training test ratio. Graphical representation of model accuracy and model loss is shown in Fig. 5.

```
Using TensorFlow backend.
(3600, 128, 128, 3)
CNN MODEL SUMMARY:

Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 128, 128, 32)      2432
_________________________________________________________________
activation (Activation)      (None, 128, 128, 32)      0
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 64, 64, 32)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 60, 60, 32)        25632
_________________________________________________________________
activation_1 (Activation)    (None, 60, 60, 32)        0
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 30, 30, 32)        0
_________________________________________________________________
dropout (Dropout)            (None, 30, 30, 32)        0
_________________________________________________________________
flatten (Flatten)            (None, 28800)             0
_________________________________________________________________
dense (Dense)                (None, 128)               3686528
_________________________________________________________________
activation_2 (Activation)    (None, 128)               0
_________________________________________________________________
dense_1 (Dense)              (None, 50)                6450
_________________________________________________________________
activation_3 (Activation)    (None, 50)                0
_________________________________________________________________
dense_2 (Dense)              (None, 2)                 102
_________________________________________________________________
activation_4 (Activation)    (None, 2)                 0
=================================================================
Total params: 3,721,144
Trainable params: 3,721,144
Non-trainable params: 0
_________________________________________________________________
```

Figure 4: Layer-wise configurations of the applied CNN model (shape of data at each layer and the number of trainable parameters).

4.2 Detection Performance in Infrared Band

IR image recognition results resented in Table 5 appear much better than those of VL images. The best accuracy obtained is 98.12% with the original IR images as input, 100 epochs, 500 batch size and 8:2 training test partition ratio. The graphical representation of the model accuracy with loss is shown in Fig. 6.

4.3 Discussion

In this section, a comparison scenario is drawn from the results of the current research area with the obtained experimental results. Zhang et al. [23] experimented using the same dataset (only on IR images) based on deep learning, and the accuracy is 95.00%. In the experiment of Najir et al. [26], powerline recognition accuracy with HOG features is 94.00% for IR images and 83.40% for VL images. In another experiment by Gomes et al. [33], the accuracy of IR images is only 94.30%. Lee et al.

Table 4: Model building and prediction performance for different experimental setups on VL images of the PLD dataset.

Experimental Setup	**Model Building**		**Model Performance**				
Image source: Image size, Epoch: Batch size, Training: Test	Train Acc (%)	Val. Acc (%)	Recall	Precision	F1-score	Acc (%)	RMSE
VL(Gray):128×128, 100:500, 3200:800	79.84	93.96	74.75	74.87	74.71	74.75	–
VL(Gray):128×128, 100:500, 3200:800	93.00	96.00	89.00	89.00	89.00	89.00	–
VL(Color):128×128, 50:500, 3600:400	94.06	99.92	86.00	86.00	86.00	86.37	–
VL(Color):128×128, 100:500, 3600:400	94.72	96.29	90.50	90.64	90.57	90.50	–
VL(Original):128×128, 50:500, 3200:800	99.97	96.25	87.50	87.50	87.49	86.75	0.3640
VL(Original):128×128, 100:500, 3200:800	99.97	96.25	87.50	87.50	87.49	87.50	0.3535
VL(Original):128×128, 100:500, 3200:800	**1.00**	**94.17**	**91.75**	**92.13**	**91.73**	**91.75**	**0.8250**

Table 5: A brief outline of obtained Performance of employed Deep CNN on IR images for power-line detection along with other experimental details

Experimental Setup	**Model Building**		**Model Performance**				
Image source: Image size, Epoch: Batch size, Training: Test	Train Acc (%)	Val. Acc (%)	Recall	Precision	F1-score	Acc (%)	RMSE
IR(Gray):128×128, 50:500, 3200:800	93.91	95.95	95.53	95.58	95.00	95.38	–
IR(Gray):128×128, 100:500, 3200:800	93.91	96.00	95.87	96.00	95.00	95.88	–
IR(Color):128×128, 50:500, 3600:400	99.08	98.06	97.50	97.50	97.49	97.50	0.1581
IR(Color):128×128, 100:500, 3600:400	1.00	98.89	98.75	98.75	98.74	98.75	0.1110
IR(Original):128×128, 50:500, 3200:800	99.97	97.19	98.12	98.12	98.12	98.12	0.1369
IR(Original):128×128, 100:500, 3200:800	1.00	98.12	98.12	98.13	98.12	98.12	0.1369
IR(Original):128×128, 100:500, 3200:800	**1.00**	**98.91**	**99.12**	**99.13**	**99.12**	**99.12**	**0.0935**

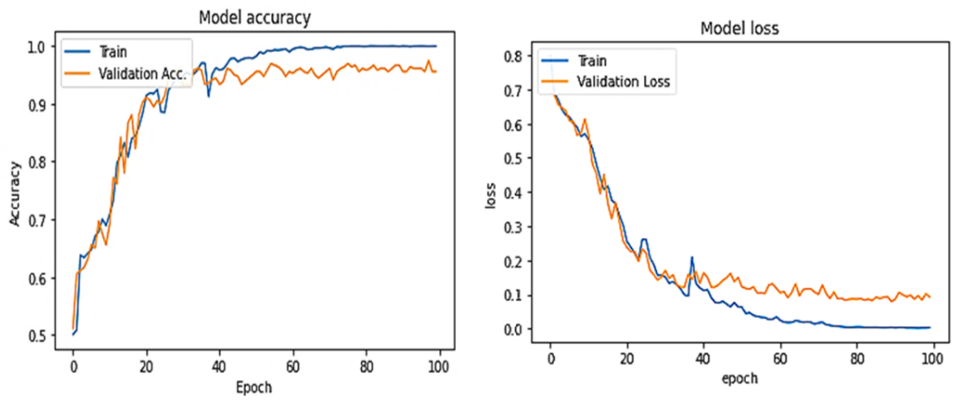

Figure 5: Graphical representation of training vs. validation accuracy and loss concerning several epochs during training with 9:1 ratio for VL images.

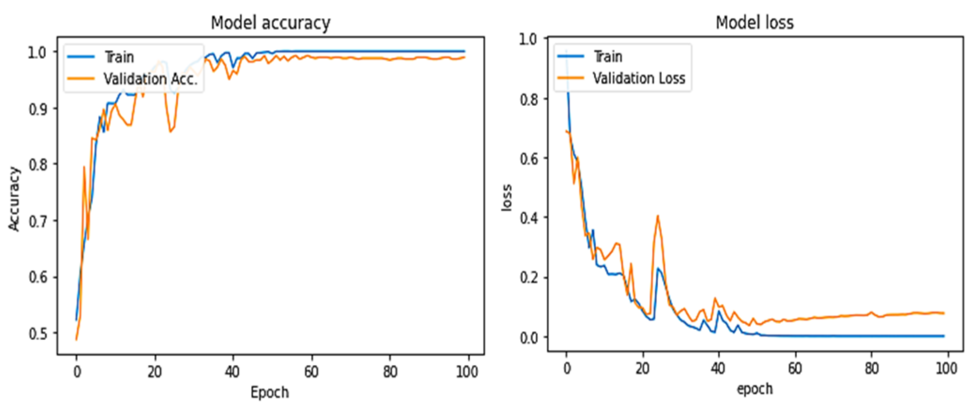

Figure 6: Graphical view of accuracy and loss with epochs during training as well as validation for IR images.

[34] have reported experiments on both VL and IR images on the PLD dataset, that produced recognition accuracy of 58.70% on VL images and 64.81% on IR images. The proposed CNN-based method gives an accuracy of 91.75% on VL images and 99.12% on IR images.

Table 6: Comparison with state-of-the-art for recognition results on VL and IR images of PLD dataset

Dataset	Method	Recall	Precision	F1-score	Acc (%)	RMSE
VL	Lee et al.[34]	78.78	78.46	-	58.70	-
	Seikh et al.[26]	81.13	87.05	83.98	83.40	-
	Our method	**91.75**	**92.13**	**91.73**	**91.75**	**0.0813**
IR	Gomes et al.[33]	-	-	-	94.30	-
	Zhang et al.[23]	-	-	-	95.00	-
	Seikh et al.[26]	92.59	95.65	94.10	94.00	-
	Our method	**99.12**	**99.13**	**99.12**	**99.12**	**0.0935**

5 Conclusion

This paper proposed a CNN-based recognition process to detect power lines. The pairwise classification problem is a classification with two categories problem that is applied to the power line recognition problem. The two classes of the given problem are: (a)The power line exists in the image. (b)The power line does not exist in the image. This method can also be applied in the real world by activating an alarm whenever a power line is detected or is near the flying vehicle. The proposed method is evaluated on the power line image dataset. This dataset contains 8000 images from these 4000 VL images and 4000 IR. The accuracy that we get after applying the proposed CNN model is 91.75% for 99.12 % IR images and VL images. Compared with state-of-the-art results, the proposed results are more satisfactory than those of other experimental results. In the near future, we will reduce the false negative rate and use another CNN model to improve the accuracy rate of recognition of VL images of the PLD dataset.

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