Real-time On-board Detection of Components and Faults in an Autonomous UAV System for Power Line Inspection

Naeem Ayoub[a] and Peter Schneider-Kamp[b]
Department of Mathematics and Computer Science, University of Southern Denmark, Odense, Denmark

Keywords: Power Lines Inspection, Fault Detection, Autonomous Drones Systems, Deep Learning.

Abstract: The inspection of power line components is periodically conducted by specialized companies to identify possible faults and assess the state of the critical infrastructure. UAV-systems represent an emerging technological alternative in this field, with the promise of safer, more efficient, and less costly inspections. In the Drones4Energy project, we work toward a vision-based beyond-visual-line-of-sight (BVLOS) power line inspection architecture for automatically and autonomously detecting components and faults in real-time on board of the UAV. In this paper, we present the first step towards the vision system of this architecture. We train Deep Neural Networks (DNNs) and tune them for reliability under different conditions such as variations in camera used, lighting, angles, and background. For the purpose of real-time on-board implementation of the architecture, experimental evaluations and comparisons are performed on different hardware such as Raspberry Pi 4, Nvidia Jetson Nano, Nvidia Jetson TX2, and Nvidia Jetson AGX Xavier. The use of such Single Board Devices (SBDs) is an integral part of the design of the proposed power line inspection architecture. Our experimental results demonstrate that the proposed approach can be effective and efficient for fully-automatic real-time on-board visual power line inspection.

SCITEPRESS
SCIENCE AND TECHNOLOGY PUBLICATIONS

1 INTRODUCTION

Visual inspections of power lines and the various components of power pylons are essential to ensure the uninterrupted functioning of the power grid. Most companies are using manual inspection methods involving humans, helicopters or manually-piloted UAVs. These types of inspection are rather expensive and slow, with some of them even being outright dangerous. To overcome these issues, research projects at some companies as well as in the academic world are focusing on the development of Artificial Intelligence (AI)-based autonomous power lines inspection and fault detection methods. In recent years, a lot of focus has been on inspection architectures that partially automate the visual inspections by utilizing drones or climbing robots (Jenssen et al., 2018). The increase of computational capabilities of SBDs and the extended capabilities of UAV technologies have lead many researchers to focus and develop UAVs based autonomous object detection systems. There is a stream of research on vision-based applications for UAVs (Al-Kaff et al., 2018), which provides the potential to become a game changer in the inspection of power lines.

Based on recent advances in drones technology, in this paper, we address a number of challenges regarding traditional power line inspection methods and develop autonomous algorithms by utilizing Deep Learning (DL) technology. We also create a medium-sized dataset of different classes based on normal and faulty components (Figure 1) for training the semi-supervised classification models. During the development of the proposed architecture, we identified that there can be different factors that influence the inspection process: training data, the relatively small size of components and faults, unidentified faults, and cluttered backgrounds in different lighting conditions.

2 BACKGROUND

In this section, we discuss different power line inspection method and DL-based object detection methods. These provide the real-world as well as the academic background for our proposed solution.

[a] https://orcid.org/0000-0002-7387-4441
[b] https://orcid.org/0000-0003-4000-5570

Ayoub, N. and Schneider-Kamp, P.
Real-time On-board Detection of Components and Faults in an Autonomous UAV System for Power Line Inspection.
DOI: 10.5220/0009826700680075
In *Proceedings of the 1st International Conference on Deep Learning Theory and Applications (DeLTA 2020)*, pages 68-75
ISBN: 978-989-758-441-1
Copyright © 2020 by SCITEPRESS – Science and Technology Publications, Lda. All rights reserved

Figure 1: Sample images of normal and related most common faulty components classes used to train the DNNs model (from top left to the right bottom): Insulator type 1, Insulator type 2, Insulator type 3, damaged insulator, normal Vibration Dampener (VD), damaged VD, missing VD, normal Nutbolt, rusted Nutbolt, normal Toppads (Jenssen et al., 2018), missing Toppads (Jenssen et al., 2018), Antena, broken Wire, Bird Nest, respectively.

2.1 Power Line Inspection Methods

Power lines are traditionally inspected at regular intervals by different inspection methods such as human-centered power lines inspection, semi-automated power line inspection, and UAV-based power line inspection methods (Jenssen et al., 2018).

2.1.1 Human-centered Power Line Inspections

Human-centered power line inspection methods rely on human involvement in the form of inspectors. In these methods, the inspection of power lines is conducted by foot patrols or by helicopter-assisted surveys. When using the foot patrol method, a team typically consists of two or more inspectors travelling along the power lines by foot and inspect the power lines with the help of binoculars or infrared cameras. Where a closer look is required, the power line is shut down, and one of the inspectors climbs the power tower and along the power line secured by a rope.

When using the helicopter-assisted inspection method, a team of inspectors travel by helicopter along power lines to take pictures of different components of pylons. These images are further sent to inspectors for offline inspection. The inspectors then identify the faults such as rusty components, birds nests, broken wires, faulty and broken insulators, missing toppads, and other misformed or missing components.

These two inspection methods are human-centered and are still widely used by inspection companies in spite of a number of disadvantages such as high cost, extensive time consumption, lack of safety in harsh terrains, and even impossibility of application in less than optimal weather conditions. The accuracy is rather low due to many components being hard to reach by humans or helicopters. The biggest disadvantage of helicopter-based inspection in addition to very high costs is that flying close to power lines poses a life-threatening security risk as contact with the cables during survey usually has fatal consequences (Takaya et al., 2019).

2.1.2 Semi-automated Power Line Inspections

Human-centered inspections are performed less frequently because of their high monetary and time costs. As an alternative to these manual inspections, semi-automated inspection methods are slowly being used by a few first-moving inspection companies. These methods provide a moderate boost to the speed of the inspection process, improve the accuracy, and moderately reduce the inspection costs. The most common techniques are semi-automated helicopter-assisted and climbing-robots inspections. Automated helicopter-assisted inspections differ from manual helicopter-assisted inspections, because, in this method, vision-based object detection techniques are used after the collection of the inspection images and videos. For example, power mast detection can be applied for guiding cameras to automatically film the conductors, pylons, power components, and objects around the pylons and under the power lines (Bühringer et al., 2010). Although, this technique has reduced the dependency on human inspectors for visual observation and sped up the inspection process, inspection costs are still high, and safety issues remain challenging. To overcome these challenges, climbing robots inspection techniques has been adopted by different companies. In this method, climbing robots carrying many sensors and cameras travel on power-lines for inspection. Zhou et al. (Zhou et al., 2016) indicated that climbing robots can lead to new challenges during inspection such as damaging the power-wires while traveling, difficulties while crossing obstacles on and around wires, and comparatively large time costs compared to the automated helicopter-assisted inspection method.

2.1.3 UAV-based Power Line Inspections

UAV-based power line inspections are the most promising inspection method. Developing the technology to be more robust is one of the main challenges for many researchers and companies. In this method, UAVs are equipped with multiple cameras and sensors to travel along the power lines to inspect them and detect faults. This technology has made a some progress during the last few years because it has overcome most of the inspection challenges such as the cost of inspections as well as inspection safety and speed.

2.2 DL Models for Object Detection

During the last two decades, many researchers have proposed different ML (Machine Learning)- and DL (Deep Learning)-based computer vision algorithms by considering supervised, semi-supervised, and unsupervised methods. DL-based object detection techniques are very popular these days. These advances in vision based techniques are encouraging the power industry to consider replacing the traditional inspection methods and develop autonomous power lines monitoring systems based on the use UAVs. The main reason of building the autonomous inspection systems is its property of being able to detect a wide range of components and faults on a single inspection (Zhou et al., 2019b). Reviews of different data sources for vision-based inspection and existing vision-based inspection systems can be found in (Contreras-Cruz et al., 2019)

2.3 The Challenges Ahead

In this era of AI (Artificial Intelligence), as researchers are making much progress in developing autonomous systems, real-time autonomous power line inspection using UAVs is still a big challenge. Many researchers are developing Deep Learning (DL)-based computer vision algorithms to automate the inspection process (Agnisarman et al., 2019). Some researchers have applied these vision based method for power line inspections (Zhou et al., 2019a) (Azevedo et al., 2019) (Nguyen, 2019). However, the current UAV-based power lines inspection techniques are still facing many unsolved challenges (Jenssen et al., 2019) (Gao et al., 2019). Alhassan et al. (Alhassan et al., 2020) presented a review and pointed at the challenges during power line inspections. During the initial development phase of our architecture, we identified five main challenges that need to be addressed for building UAV-based autonomous monitoring systems:

- Data collection and data analysis
- Autonomous vision systems for UAVs to perform real-time inspection
- Suitable SBDs with sufficiently strong GPU to run vision-based DL models for real-time on-board inspection
- Communication and mission control systems for BVLOS UAV systems
- Deep integration of path planning and control systems in a visual UAV-based inspection system

In this paper, we focus on the first three challenges, which are essential for designing and implementing an autonomous visual real-time on-board inspection system. We will discuss the remaining two challenges in future work. Note, though, that in particular the fifth point depends on the ability to run DL models on-board and in real time to achieve a deep integration, e.g., by reusing component and fault detection results for adapting the path planning and the further collection of images. To address first three challenges, we collected images data for different components and faults. Then we trained DL models on the collected and partially human-labelled images. Experiments on different hardware during field test phase shows that the proposed architecture can provide a solid base for building autonomous power lines inspection systems. Figure 2 shows the flowchart of our proposed architecture for autonomous power line inspection.

The remainder of this paper is structured as follows: Section 3 presents relevant related work on different DL-based classification techniques for object detection. Our proposed autonomous power line inspection architecture and experimental results are described in Section 4. Finally, we conclude our results and further work in Section 5.

SCITEPRESS SCIENCE AND TECHNOLOGY PUBLICATIONS

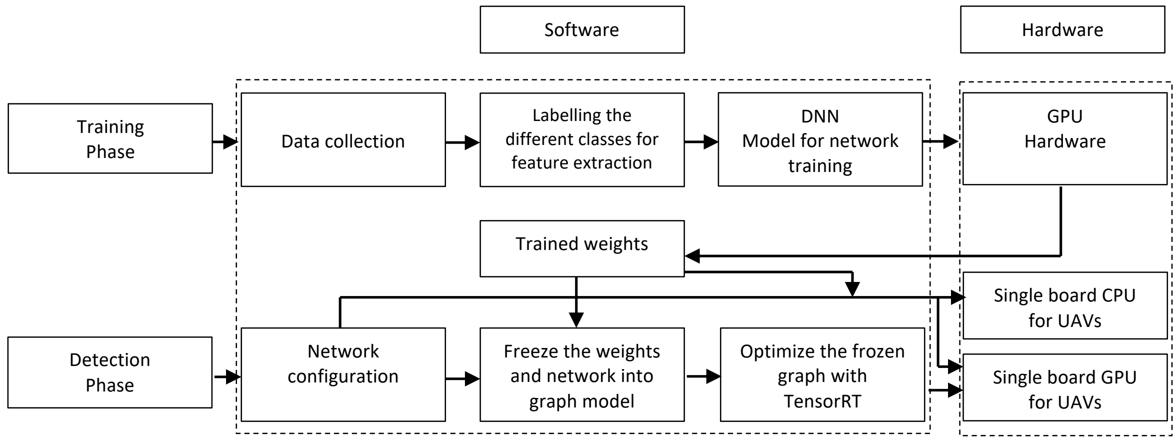

Figure 2: Proposed architecture for UAVs based on-board inspection and autonomous vision system.

3 RELATED WORK

3.1 DL-based Objects Classification and Detection Models

During last few years, Convolutional Neural Networks (CNNs) have been used for different computer vision techniques such as object detection (Zou et al., 2019) as well as image classification and semantic segmentation (Li et al., 2016).

The CNN model has been improved in a variety of ways, and state-of-the-art object detection algorithms based on CNNs are flourishing. As CNN models are computationally rather expensive, it is not straightforward to use them in real-time image processing, in particular, in situations where computational resources are limited such as SBDs on board of UAVs. In this section, we briefly discuss some CNN frameworks developed for classification and detection of objects relevant to the development paper.

R-CNN: To improve the computational efficiency, Girshik et al. (Girshick et al., 2014) proposed the R-CNN method for object detection. In this method, region proposals obtained by selective search methods, and then features are extracted with a CNN. A classifier based on support vector machines is used to classify these features. Finally, patches are optimized by bounding box regression. Figure 3 shows the flow chart of an RCNN model (reproduced from (Girshick et al., 2014).

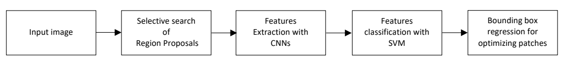

Figure 3: Flow chart of R-CNN model.

ResNet: The training of CNNs remained a challenging in the above mentioned variants of CNNs. To ease the training of neural networks, He et al. (He et al., 2016) introduced the Deep Residual Network (ResNet) model. In this method, connections between the standard CNN layers allow the gradient signal to travel back directly from later layers to early layers. During the learning phase, the connection establishment technique of ResNet layers allow the network model to successfully train even with 152 layers. Figure 4 shows the residual learning model (reproduced from (He et al., 2016)).

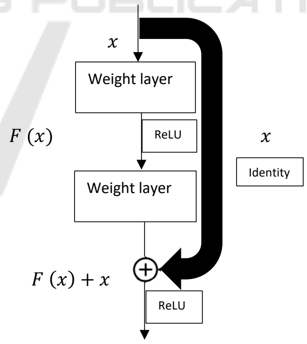

Figure 4: Residual learning model.

R-FCN: Dai et al. (Dai et al., 2016) introduced a new method based on Region-based Fully Convolutional Networks (R-FCNs) to address existing issues in R-CNN-based network architectures. As an alternative of applying region-level feature extraction, R-FCN adopts a FCN (Fully Conovolutional Network) architecture to share the computations across the image. In this method, position-sensitive score maps are obtained for classification and detection in a single evaluation. R-FCN perform 2.5-20 times faster and achieve higher accuracy than the Faster R-CNN.

Figure 5 show the architecture of R-FCN (reproduced from (Dai et al., 2016)).

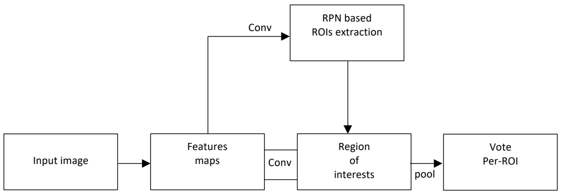

Figure 5: Region-based Fully Convolutional Network model.

YOLO: Redmon et al. (Redmon et al., 2016) proposed a real-time object detection algorithm YOLO (You Only Look Once). This model unifies region classification proposals into a single neural network to predict the bounding boxes and class probabilities. A single image is divided into $S \times S$ grid cells and detection is performed into single evaluation. This unique network structure makes YOLO much faster than the aforementioned algorithms.

To improve accuracy, the YOLOv2 (Redmon and Farhadi, 2016) model was proposed, in which features such as direct location prediction, a high resolution classifier, fine gradients, and dimension clustering are added to the YOLO network. The authors introduced batch normalization, direct location prediction and replaced the fully connected layer with a convolution layer to speed up the training and detection process. In 2018, Redmon et al. introduced YOLOv3 (Redmon and Farhadi, 2018) to further improve the accuracy of YOLO and added more layers and features to the network. In this paper, for building the autonomous vision part of the proposed UAV-based inspection architecture, we have taken into consideration both speed and accuracy. For these reasons, we have used the DL model of YOLOv3 (Redmon and Farhadi, 2018) for training the autonomous vision system.

4 PROPOSED ARCHITECTURE FOR REAL-TIME ON-BOARD VISUAL INSPECTION

Our architecture for the autonomous vision system for power line inspection is based on the three following main components:

- Collection and pre-analysis of a dataset.
- Application of DL algorithms for training, testing, and analysis of the dataset.
- Selection of suitable SBDs for running the inference in real-time on board of the UAV.

In this section, we will discuss and summarize relevant data and classes of components and faults for training the autonomous detection algorithms. Then we will discuss the DL model for autonomous inspection. We will summarize different SBDs and their compatibility issues with respect to their application for UAV-based real-time inspection. We will also highlight the advantages of using SBDs with GPUs embedded within UAVs.

4.1 Data Collection and Pre-analysis

Data collection and labeling the components of different classes for training the DNN model is challenging because there are no publicly available datasets. After comprehensively reviewing different data sources and structure of the components, we have built a custom dataset with the help of an inspection company that is a collaborator in the Drones4Energy project. While collecting the image dataset, we have considered different types of components and faults as separate classes according to their appearance in different background, angles, lighting, and weather conditions. Figure 1 shows different components of power lines and their related faults reproduced from (Jenssen et al., 2018). In our dataset, we have concentrated on five relevant classes to keep the time consumption for labelling by human experts at a reasonable level.

4.2 Suitable SBDs for UAV-based Real-time On-board Inspections

Real-time on-board autonomous monitoring systems for power lines consist of two main components: DL algorithms and UAVs with embedded SBDs to run the DL algorithms. Taking into consideration the required computational power, we have trained the DL models using more powerful hardware than available for the detection process as discussed in the following.

Nvidia Tesla V100: Training DL models in reasonable time requires rather powerful GPUs. We have used an Nvidia Tesla V100 having 32GB RAM through the CUDA 10 framework. In this GPU, each streaming multiprocessor is partitioned into four processing blocks. Each block consists of two Tensor Cores, 16 FP32 cores, 8 FP64 cores, 16 INT32 cores and one Special Function Unit (SFU). This GPU has a total of 640 Tensor Cores, which jointly can accelerate the DL framework up to 125 TFLOPs (Markidis et al., 2018).

We have used a variety of different SBDs to perform inference with the DL model in order to assess and compare the real-time performance. Figure 6

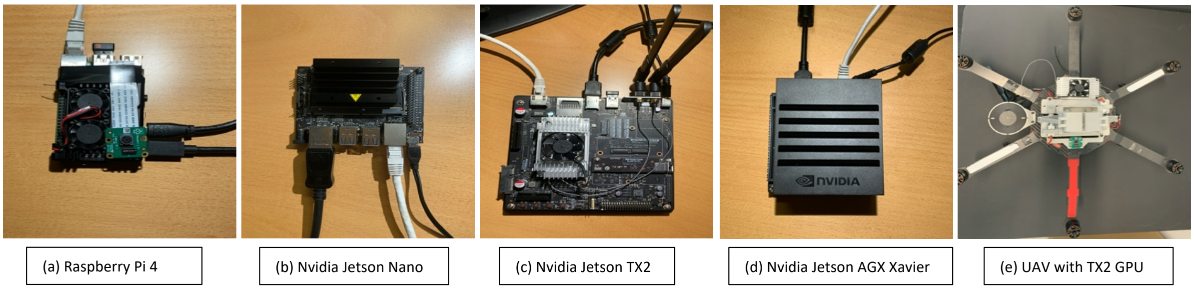

Figure 6: Single board hardware for UAVs to run real-time autonomous algorithm. From left to right, (a) Raspberry Pi 4, (b) Nvidia Jetson Nano, (c) Nvidia Jetson TX2, (d) Nvidia AGX Xavier and (e) UAV with Jetson TX2.

shows the different SBDs, which have been considered as candidates for being embedded in UAVs.

Raspberry Pi 4: The Raspberry Pi 4 is cheapest option in terms of price among the SBDs considered. This board is built with a 64-bit Broadcom Videocore VI GPU and a quad-core Cortex-A72 (ARM v8) CPU and has 4 GBs of RAM (see Figure 6(a)).

Nvidia Jetson Nano: The Jetson Nano is a small, more powerful SBD developed by Nvidia (see Figure 6(b)). It features a Maxwell architecture-based GPU and a quad-core ARM Cortex-A57 CPU and, as the Raspberry Pi 4, has 4 GBs of RAM. The GPU comes with a total of 128 Cuda cores, which can accelerate the DL framework up to 0.5 TFLOPs.

Nvidia Jetson TX2: The Jetson TX2 is an even more powerful SBD. Nvidia has equipped it with a more modern Pascal architecture-based GPU (see Figure 6(c)). The Jetson TX2 has two CPUs: a dual-Core NVIDIA Denver and a quad-core ARM Cortex-A57, sharing 8 GBs of RAM. The GPU comes with a total of 256 Cuda cores, which can accelerate the DL framework up to 1.3 TFLOPs.

Nvidia AGX Xavier: Nvidia's flagship SBD, the AGX Xavier, is one of the most powerful SBDs on the market (see Figure 6(d)). It has a Volta architecture-based GPU with a total of 512 cuda cores and 64 Tensor cores. It also has an 8-core NVIDIA Carmel ARM v8.2 64-bit CPU. The AGX Xavier can reach up to 32 TFLOPs and is specifically designed for running inference on DL models in real-time environments. The board can work in a number of different power modes, which gives the user the possibility to select the number of working CPU cores and, thereby, to control the power consumption of the SBD.

4.3 Autonomous DL Algorithm for Real-time Inspection

For training the autonomous algorithm, we have used the network model of YOLOv3 (darknet-53) proposed by Redmon et al. (Redmon and Farhadi, 2018). We also train the YOLOv3-tiny (darknet-19) model for performance comparisons. YOLOv3-tiny has fewer convolutional layers than YOLOv3, which improves its suitability for real-time processing but reduces the accuracy somewhat. Concerning the parameters, we use the default configurations of both YOLOv3 and YOLOv3-tiny. We set the momentum of the stochastic gradient descent to 0.9 and the learning rate to 0.001. The weight decay is set to 0.005. Concerning the scaling of the images for training of the network, we set the images size to 608, 416 (standard), and 288. The batch size is set to 64 to improve utilization of the GPU and its memory. During the training, we ignore the anchors that drop below the threshold value. As training needs a rather powerful GPU, we have used the Nvidia Tesla V100 GPU to train the DL models. To run the inference faster on the SBDs, we accelerate the DL algorithm using the TensorRT library. TensorRT is a DL library introduced by Nvidia that optimizes the trained weights. For optimization, the trained weights are frozen, and then these frozen weights are optimized with TensorRT. The optimized weights run much faster than non-optimized weights (compare Tables 1 and 2).

4.4 Experimental Results and Discussion

For evaluation of the real-time image processing, we have used different SBDs, which can be embedded as part of UAVs. Tables 1, 2, and 3 show the experimental evaluation in terms of frames per second (FPS) using different hardware for running real-time inference with the DL algorithms. Table 1 shows the FPS during real-time processing with YOLOv3-tiny on different hardware. YOLOv3-tiny runs much faster than the YOLOv3 model (compare Tables 2 and 3), but it provides somewhat less accuracy during inspection. The accuracy drops even more after weight optimization. We can clearly see that the processing of the algorithm with non-optimized weights is too slow for real-world implementation (see Table 1), even when only using YOLOv3-tiny. We could not run inference

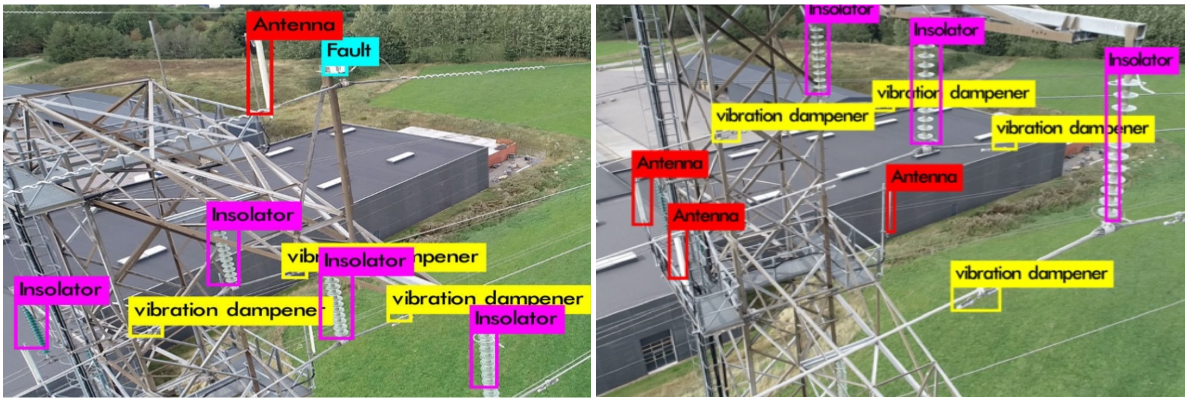

Figure 7: Results of detecting different components of power line pylons.

with the full YOLOv3 model on all SBDs due to too large memory demands.

Table 1: FPS on different scales of images during real-time detection (YOLOv3-tiny without weight optimization).

DL model	YOLOv3-tiny normal		
Input size SBD	(288)	(416)	(608)
Raspberry Pi 4	3	1	0.2
Nvidia Jetson nano	3.4	1.2	0.5
Nvidia Jetson TX2	20	17	10
Nvidia AGX Xavier	30	21.6	14

Table 2: FPS for YOLOv3-tiny on different scales of images during real-time detection with optimized weights.

DL model	YOLOv3-tiny optimized		
Input size SBD	(288)	(416)	(608)
Nvidia Jetson Nano	22	15	4.5
Nvidia Jetson TX2	25	19	12
Jetson AGX Xavier	50	32	22

Table 3: FPS for YOLOv3 on different scales of images during real-time detection with optimized weights.

DL model	YOLOv3 optimized		
Input size SBD	(288)	(416)	(608)
Nvidia Jetson Nano	5.28	3	1.45
Nvidia Jetson TX2	11.4	6.4	3
Jetson AGX Xavier	24	17	11

After optimizing weights with the TensorRT library, the performance on the Nvidia Jetson TX2 and the Jetson AGX Xavier improves significantly (see Tables 2 and 3).

We know that a DL algorithm for an autonomous vision system should have both properties: accuracy and real-time suitability. Hence, during as a result of our experimental evaluation, we choose the full YOLOv3 model with an Nvidia Jetson AGX Xavier for the real-world implementation of our vision system in the inspection architecture. The Jetson AGX Xavier can run the YOLOv3 algorithm up to 17 FPS on images scaled to 416 pixels with a good accuracy. Such a frame rate is acceptable for real-time processing and allows the drone control software to react to the results of the detection without undue delay. The experiments are performed by setting all SBDs to maximum performance mode (nvpmodel), i.e., all CPU and GPU cores were enabled at full speed. Figure 7 shows examples of the detection results for different classes of components of power lines.

SCIENCE AND TECHNOLOGY PUBLICATIONS

5 CONCLUSIONS

In this study, we have proposed and evaluated the use of autonomous DL algorithms running in real-time on board of UAVs with the purpose of visual power line inspection. We have also compared the results between different SBDs that can be embedded in UAVs for running inference for powerful DL models. We have also compared real-time results between YOLOv3-tiny (darknet-19) and YOLOv3 (darknet-53) and investigated the real-world impact of weight optimization using TensorRT.

We have given the theoretical description of different algorithms and SBDs, and then practically implemented each algorithm on these SBDs. We realized that YOLOv3 performs at an acceptable level in terms of accuracy and real-time processing on the Nvidia Jetson AGX Xavier, which therefore will constitute the SBD for the Drones4Energy project.

In the future, we will extend our work by considering the remaining two challenges of performing multiple tasks on a single UAV regarding path planning, communication, and control as well as autonomously sending and further processing the results of component and fault detection through a cloud service.

ACKNOWLEDGEMENTS

The presented research was supported by the Innovation Fund Denmark, Grand Solutions, under grant agreement No. 8057-00038A Drones4Energy project [1].

REFERENCES

Agnisarman, S., Lopes, S., Madathil, K. C., Piratla, K., and Gramopadhye, A. (2019). A survey of automation-enabled human-in-the-loop systems for infrastructure visual inspection. *Automation in Construction*, 97:52 – 76.

Al-Kaff, A., Martín, D., García, F., de la Escalera, A., and Armingol, J. M. (2018). Survey of computer vision algorithms and applications for unmanned aerial vehicles. *Expert Systems with Applications*, 92:447 – 463.

Alhassan, A. B., Zhang, X., Shen, H., and Xu, H. (2020). Power transmission line inspection robots: A review, trends and challenges for future research. *International Journal of Electrical Power & Energy Systems*, 118:105862.

Azevedo, F., Dias, A., Almeida, J., Oliveira, A., Ferreira, A., Santos, T., Martins, A., and Silva, E. (2019). Lidar-based real-time detection and modeling of power lines for unmanned aerial vehicles. *Sensors*, 19(8):1812.

Bühringer, M., Berchtold, J., Büchel, M., Dold, C., Bütikofer, M., Feuerstein, M., Fischer, W., Bermes, C., and Siegwart, R. (2010). Cable-crawler–robot for the inspection of high-voltage power lines that can passively roll over mast tops. *Industrial Robot: An International Journal*.

Contreras-Cruz, M. A., Ramirez-Paredes, J. P., Hernandez-Belmonte, U. H., and Ayala-Ramirez, V. (2019). Vision-based novelty detection using deep features and evolved novelty filters for specific robotic exploration and inspection tasks. *Sensors*, 19(13):2965.

Dai, J., Li, Y., He, K., and Sun, J. (2016). R-FCN: object detection via region-based fully convolutional networks. *CoRR*, abs/1605.06409.

Gao, Z., Yang, G., Li, E., Shen, T., Wang, Z., Tian, Y., Wang, H., and Liang, Z. (2019). Insulator segmentation for power line inspection based on modified conditional generative adversarial network. *Journal of Sensors*, 2019.

Girshick, R., Donahue, J., Darrell, T., and Malik, J. (2014). Rich feature hierarchies for accurate object detection and semantic segmentation. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 580–587.

[1] https://drones4energy.dk/

He, K., Zhang, X., Ren, S., and Sun, J. (2016). Deep residual learning for image recognition. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*.

Jenssen, R., Roverso, D., et al. (2018). Automatic autonomous vision-based power line inspection: A review of current status and the potential role of deep learning. *International Journal of Electrical Power & Energy Systems*, 99:107–120.

Jenssen, R., Roverso, D., et al. (2019). Intelligent monitoring and inspection of power line components powered by uavs and deep learning. *IEEE Power and Energy Technology Systems Journal*, 6(1):11–21.

Li, Y., Hao, Z., and Lei, H. (2016). Survey of convolutional neural network. *Journal of Computer Applications*, 36(9):2508–2515.

Markidis, S., Der Chien, S. W., Laure, E., Peng, I. B., and Vetter, J. S. (2018). Nvidia tensor core programmability, performance & precision. In *2018 IEEE International Parallel and Distributed Processing Symposium Workshops (IPDPSW)*, pages 522–531. IEEE.

Nguyen, V. N. (2019). Advancing deep learning for automatic autonomous vision-based power line inspection.

Redmon, J., Divvala, S., Girshick, R., and Farhadi, A. (2016). You only look once: Unified, real-time object detection. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*.

Redmon, J. and Farhadi, A. (2016). Yolo9000: Better, faster, stronger. *arXiv preprint arXiv:1612.08242*.

Redmon, J. and Farhadi, A. (2018). Yolov3: An incremental improvement. *CoRR*, abs/1804.02767.

Takaya, K., Ohta, H., Kroumov, V., Shibayama, K., and Nakamura, M. (2019). Development of uav system for autonomous power line inspection. In *2019 23rd International Conference on System Theory, Control and Computing (ICSTCC)*, pages 762–767. IEEE.

Zhou, G., Yuan, J., Yen, I.-L., and Bastani, F. (2016). Robust real-time uav based power line detection and tracking. In *2016 IEEE International Conference on Image Processing (ICIP)*, pages 744–748. IEEE.

Zhou, M., Li, K., Wang, J., Li, C., Teng, G., Ma, L., Wu, H., Li, W., Zhang, H., Chen, J., et al. (2019a). Automatic extraction of power lines from uav lidar point clouds using a novel spatial feature. *ISPRS Annals of Photogrammetry, Remote Sensing & Spatial Information Sciences*, 4.

Zhou, X., Fang, B., Qian, J., Xie, G., Deng, B., and Qian, J. (2019b). Data driven faster r-cnn for transmission line object detection. In *Cyberspace Data and Intelligence, and Cyber-Living, Syndrome, and Health*, pages 379–389. Springer.

Zou, Z., Shi, Z., Guo, Y., and Ye, J. (2019). Object detection in 20 years: A survey. *CoRR*, abs/1905.05055.