Method for detecting surface defects of runner blades of large hydraulic turbines based on improved real-time lightweight network

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Abstract. Cavitation erosion, wears and cracks caused by residual thermal stress occur during the operation of hydropower units. It is a key scientific problem that needs to be solved urgently to detect defects in the foundation pit of hydropower units. In this paper, a mobile robot is used to obtain the surface image of the over-current parts of hydropower units, and deep learning algorithm is used to detect defects. In order to detect blade surface defects more safely, reliably, efficiently and quickly, this paper proposes an improved real-time lightweight convolutional neural network MobileNetv3-YOLOv4-Lite, which is suitable for portable embedded devices. In this paper, MobileNetv3 is selected to replace CSPDarkNet53 as the new backbone extraction network, and all standard convolutions are replaced by depth separable convolutions. Compared with CSPDarkNet53, MobileNetv3 only needs 37.35MB in weight, which is 206.94MB lower. It shows that the network proposed in this paper has the advantage of low memory and can run on CPU. The defect detection accuracy of MobileNetv3-YOLOv4-Lite can reach 97.48%, and the GPU can process 3024x4023 images, which can process 44 images in one second. The standard convolution of the enhanced feature extraction layer network is replaced by the depth separable convolution, and the parameter quantity is reduced by 29.33%. Therefore, it can be considered that the real-time lightweight convolutional neural network MobileNetv3-YOLOv4-lite proposed in this paper can detect the surface defects of turbine blades well.

1. Introduction
As an important part of hydroelectric generating set, turbine runner is not only the core of energy conversion, but also affects the hydraulic performance and reliability of the whole set. The transportation of large turbine runner is limited by traffic, so most of them are assembled and welded at the installation site of the unit after the single blade is manufactured in the production enterprise. However, the welding stress can not be eliminated by heat treatment in the field, so that defects will occur on the runner working face due to the welding stress, nonlinear pulse force of water flow, sand erosion and cavitation in the running process. When the defects extend to a certain extent, the vibration of the turbine will increase, the cavitation at the water outlet of the back of the blade will accelerate the wear of the blade working face, which greatly reduces the power generation efficiency
of the turbine. In addition, there are great potential safety hazards in the running process of the turbine unit. If they occur,

At present, most of the methods used in turbine runner blade detection are manual detection, but the accuracy of manual detection is low, the cost is high, and the work risk is high. During manual inspection, the turbine needs to stop running, and each manual inspection takes about one week, which will bring huge economic losses. Therefore, it is particularly important to change from traditional manual detection to machine detection. In the process of machine detection, choosing a more suitable algorithm will determine the accuracy of fault detection. Therefore, this paper is based on Mobilenet-YoloV4-Lite algorithm to defect detection of hydroturbine runner blade.

2. Related Work
Scholars at home and abroad have been studying the fault detection of wind turbines, water turbines and other related machinery. Next, some representative detection methods will be listed.

Yi considered the problem of uneven distribution in the process of sample processing, so he used MC-SMOTE algorithm to divide samples into different clusters, and then classified them and applied them to the actual industrial production problem of wind turbine blade icing. The classification results showed that MC-SMOTE had higher performance than classic SMOTE[1]. Zhang put forward a new dynamic model sensor method for wind turbine fault detection based on SCADA data, which can extract the fault characteristics of wind turbine system and apply it to turbine fault detection. The results also prove that this method has certain prediction and detection ability[2]. By using LSTM network, Yang can predict the time series data of wind turbines in normal operation. Simulation results show that this method can quickly detect possible turbine system faults[3]. Desa applied the semi-supervised learning method to the fault detection of wind turbines, using NSGA-II method to select characteristic parameters, and using Soft-Label and Binary Support Vector Machine for semi-supervised fault detection[4]. Magda collected the time domain signals from wind turbines and converted them into two-dimensional matrix to form two-dimensional images. Then, the texture features of the images were analyzed by image recognition, and these faults were classified[5]. Liu proposed an iterative nonlinear filter to eliminate heavy noise and extract weak fault vibration features. Based on morphological analysis, it is applied to fault detection of blade bearings of wind turbines[6].

At present, due to the large size of hydraulic turbines and the difficulty in collecting fault data, few scholars have studied the surface defect detection of turbine runner blades and other related contents. In this paper, the Mobilenet-YoloV4-Lite algorithm in the field of deep learning is used to detect the surface defects of turbine runner blades. The following paper is arranged as follows: Section 3 introduces Mobilenet-YoloV4-Lite algorithm and fault detection process; Section 4 introduces the experimental process and results, and finally summarizes and looks forward to it.

3. Approach

3.1. Mobilenet-YoloV4-Lite algorithm

3.1.1. MobileNet network model

The lightweight CNN network is designed to meet the requirement of improving the running speed on the premise of ensuring the accuracy of MobileNet network. Compared with the traditional convolutional neural network, the network parameters and computation are greatly reduced at the expense of slightly reduced accuracy. (Compared with VGG16, the accuracy is reduced by 0.9%, but the model parameters are only 1/32 of VGG and 1/27 of FLOPs).

The MobileNet network uses Depthwise Convolution and 1x1 Pointwise Convolution instead of traditional standard convolution. In traditional convolution, the channel of each convolution kernel is equal to the channel of the input feature matrix, while in DW convolution, the channel of each convolution kernel is equal to 1. If changing the channel of the output feature matrix, it only need to
add a PW convolution after DW convolution. A combination of Depthwise Convolution and Pointwise Convolution is called Depthwise Separable Convolution, as shown in Figure 1.

![Fig.1 Depthwise Separable Convolution](image)

The standard convolution calculation is as follows:

\[ D_K \times D_K \times M \times N \times D_F \times D_F \]  

Parameter quantity of standard convolution layer:

\[ D_K \times D_K \times M \times N \]  

Calculation amount of depth separable convolution:

\[ D_K \times D_K \times M \times D_F \times D_F + M \times N \times D_F \times D_F \]  

Depth separable convolution parameter quantity:

\[ D_K \times D_K \times M \times N + D_K \times D_K \times N \]  

Divided by 1 and 3:

\[ \frac{D_K \times D_K \times M \times N \times D_F \times D_F}{D_K \times D_K \times M \times D_F \times D_F + M \times N \times D_F \times D_F} = \frac{1}{N} + \frac{1}{D_K^2} \]  

\( D_K \) is the size of convolution kernel, \( D_F \) is the input feature graph, \( m \) is the channel of the input feature matrix, \( n \) is the channel of the output feature matrix, and DW convolution in mobilenet network uses 3x3 convolution kernel. By substituting 3x3 convolution kernel into calculation, it can be obtained that the calculation amount of depth separable convolution is about 1/9 times that of standard convolution.

When the input image size is 416×416×3 pixels and the input size is 1.98MB, the parameters of CSPDarkNet53 and MobileNet(V1, V2, V3) are compared without considering the influence of Resilient Architecture, Pooling layer, Activation function, BN layer and FC layer, as shown in Table 1.

| Network Model         | Input size/MB | Params size/MB |
|-----------------------|---------------|---------------|
| CSPDarkNet53          | 1.98          | 101.54        |
| MobileNetV1           | 1.98          | 16.14         |
| MobileNetV2           | 1.98          | 13.37         |
| MobileNetV3           | 1.98          | 11.92         |

3.1.2. Mobilenet-YoloV4-Lite network model

Yolov4-lite is suitable for real-time lightweight target detection algorithm running in portable embedded devices. Its backbone feature extraction network is composed of CSPDarkNet53, which has Resblock body module, which is composed of one-time downsampling and multi-time residual structure stacking, and uses CSPnet structure. The Backbone network is replaced by MobileNet network, and the structure of Mobilenet-YoloV4-Lite network is shown in Figure 2. Depth feature extraction prediction and prediction network consists of a series of convolution, residual structure and
upsampling. In order to further reduce the amount of parameters and computation, the 1x1 and 3x3 standard convolutions of the enhanced feature extraction network are replaced by depth separable convolutions.

In order to further reduce the amount of parameters and computation, the 1x1 and 3x3 standard convolutions of the Enhanced Feature Extraction Network (Panet) are replaced by depth separable convolutions, and the improved overall network parameters are shown in the Table 2.

| Network Model | before optimization | After optimization |
|---------------|---------------------|--------------------|
| MobileNetV1   | 4.09                | 1.26               |
| MobileNetV2   | 3.90                | 1.08               |
| MobileNetV3   | 3.99                | 1.17               |

### 3.2. Fault detection process

In the process of collecting pictures required for network training, the pictures with too large or too small resolution are removed, and only the pictures close to the input size requirements of the network are kept. Label pictures with labelImg, change them into VOC data format, train them in batch according to batch size, update and save weights by back propagation, and stop training when the training times reach the specified iteration times. The training process is shown in Figure 3.

In particular, MobileNetv3 adopts deep separable convolution and h-swish activation function. The whole network adopts SPP in layer 254 to further extract the picture features, and combines the upsampling layer with layer 181 in layer 270, and convolves it five times as the first prediction layer; Combine 69 layers with 299 layers as the second prediction layer; It Combined 268 layers with 392 layers as the third prediction layer. Finally, 1600 different defect pictures are used as data sets for training, 2080 different defect pictures are used as data sets for training.
4. Experiment and analysis

4.1. Experiment platform
Data annotation work environment: Windows 10 (AMD Ryzen 7 4800H with Radeon Graphics 8 nuclear); Memory 8GB; Graphics card is Nvidia GeForce GTX 1650 (Video memory 4GB).

Working environment of experimental network training: Ubuntu (Core i5-10400G @ 2.90GHz 6 nuclear); Kingston DDR4 2666MHz (Memory 8GB); Graphics card is Nvidia GeForce GTX 1660 SUPER (Video memory 6GB); Cuda 10.2; cudnn 7.6.

4.2. Data collection
In the daily operation and maintenance of hydraulic turbine, the time period is long, usually once a year or twice a year, and the collected blade data is very few, which can not support the data set requirements for deep learning, so we artificially made defects on the turbine blades. The main defect detection targets are cavitation (QS) and crack (Iw), the partial defect map is shown in Figure 4.

4.3. Experimental parameters
Data set: cavitation (800 pictures) and crack (800 pictures) as training set, 320 sheets are used as verification set and 160 sheets as test set. The adjustable hyperparameters in the training network are shown in the following Table 3. The learning rate of the first 1000 generations is 0.001, and that of the last 1000 generations is 0.0001.

| Parameter Name | Input size | Batch size | NMS | Width Multiplier α | Resolution Multiplier β | Freeze training learning rate | Thawing training learning rate |
|----------------|------------|------------|-----|--------------------|--------------------------|-----------------------------|------------------------------|
| Value          | 416        | 32         | 0.5 | 1.0                | 1.0                      | 0.001                       | 0.0001                       |

4.4. Experimental results and evaluation
Usually we will use AP, F1, mAP, FPS and network parameters to judge whether a network is suitable for a working condition. The formulas of AP and mAP are defined as follows:

\[
AP = \int_0^1 P(x) \, dx
\]
\[ mAP = \frac{\sum_{i} AP_i}{n} \]  

(7)

AP is the average accuracy of a defect, and mAP is the average accuracy of each defect.

According to the table 4 set the parameters of the network, and select DarkNet53, CSPDarkNet53, MobileNetv1, MobileNetv2 and MobileNetv3 as backbone network for training in yolov4-lite network. The experimental results are as follows.

After 2000 generations of each network structure, the parameters of the evaluation network can be obtained. It can be seen from the figure that the mAP of CSPDarkNet53 is 0.41% higher than that of DarkNet53, the FPS decreases by 4.53, and the weight is as high as 244.29MB, which is 7.97MB higher than that of DarkNet53. Therefore, it can be seen that taking CSPDarkNet53 as the backbone network is difficult to meet the needs of portable embedded devices. Compared with CSPDarkNet53, MobileNetv3 improves the mAP by 3.27%, improves the accuracy of network defect detection, reaches 44.68 FPS, can process 44 images in one second, improves by 27.74, and only needs 37.35MB of weight, which reduces by 206.94MB. To sum up, MobileNetv3 has higher accuracy, better speed and lower weight, and its advantages can meet the needs of portable embedded devices, therefore, Yolov4-lite chooses MobileNetv3 as the backbone network.

| Table 4 Different Backbone Network 2000 Generation Training Results |
|---------------------------------------------------------------|
| Backbone          | Defects | AP/\% | F1/\% | mAP/\% | FPS | Weight/MB |
|-------------------|---------|-------|-------|--------|-----|-----------|
| DarkNet53         | QS      | 93.03 | 95.00 | 93.80  | 21.47| 236.32    |
|                   | lw      | 94.57 | 86.00 |        |     |           |
| CSPDarkNet53      | QS      | 93.17 | 95.00 | 94.21  | 16.94| 244.29    |
|                   | lw      | 97.98 | 90.00 |        |     |           |
| MobileNetv1       | QS      | 87.12 | 75.00 | 95.75  | 38.97| 48.42     |
|                   | lw      | 100.00| 94.00 |        |     |           |
| MobileNetv2       | QS      | 90.91 | 95.00 | 94.69  | 39.00| 41.20     |
|                   | lw      | 99.01 | 69.00 |        |     |           |
| MobileNetv3       | QS      | 95.45 | 95.00 | 97.48  | 44.68| 37.35     |
|                   | lw      | 99.50 | 97.00 |        |     |           |

We selected MobileNetv3 as the backbone network, trained for 2000 generations, and identified lw and QS defects. The experimental results show that the defects can be identified quickly and accurately, and the recognition rate of lw can reach 99% and QS can reach 96%. Therefore, MobileNetv3-YoloV4-Lite can satisfy the real-time and accuracy of portable devices. As shown in Figure 5.

![Fig.5 The crack defect cavitation defect shown](image-url)
To further verify that Mobilenet-YoloV4-Lite has higher accuracy and faster detection speed in detecting surface defects of turbine impeller blades, the experiment is compared with one-stage, two-stage and anchorage-free network models, and the specific results are shown in Table 5.

| Network Model                  | mAP/%  | FPS    |
|-------------------------------|--------|--------|
| SSD-300                       | 81.78  | 33.94  |
| Faster-Rcnn-ResNet50          | 88.56  | 25.31  |
| CenterNet-ResNet50            | 84.75  | 27.27  |
| Yolov3-EfficientNet           | 94.73  | 27.70  |
| MobileNetv3-YOLOv4-Lite       | 97.48  | 44.98  |

It can be seen that the mAP and FPS of MobileNetv3-YoloV4-Lite are improved by 15.7 and 10.74 compared with SSD-300. Therefore, we think that Mobilenet-YoloV4-Lite is more suitable for detecting surface defects of impeller blades.

5. Conclusion

Paper proposes to replace the main extraction network of YOLOv4-lite with MobileNetv3, and applies it to the detection of major surface defects of large turbine impeller blades. The experimental results show that the defect detection accuracy of MobileNetv3-YOLOv4-Lite can reach 97.48%, and the weight of MobileNetv3 is reduced by 206.94MB compared with CSPDarkNet53, which shows that MobileNetv3-YOLOv4-Lite network proposed by paper has the advantages of high detection rate and low memory storage. The mAP of MobileNetv3-YoloV4-Lite is much higher than that of SSD-300 and FPS; GPU processes more high-resolution pictures per second than CenterNet-ResNet50. Therefore, it can be considered that the real-time lightweight convolutional neural network MobileNetv3-YOLOv4-lite proposed in this paper is more accurate and faster in detecting surface defects of turbine blades.

References

[1] H. Yi, Q. Jiang, X. Yan and B. Wang, "Imbalanced Classification Based on Minority Clustering SMOTE with Wind Turbine Fault Detection Application," in IEEE Transactions on Industrial Informatics.
[2] Zhang, Sikai, Lang, Zi-Qiang. SCADA-data-based wind turbine fault detection: A dynamic model sensor method[J].Control Engineering Practice, v 102, September 2020.
[3] T. Yang, J. Teng, C. Li and Y. Feng, "Wind turbine fault detection and diagnosis using LSTM neural network," 2020 39th Chinese Control Conference (CCC), Shenyang, China, 2020, pp. 4042-4047.
[4] F. P. G. de Sá, D. N. Brandão, E. Ogasawara, R. d. C. Coutinho and R. F. Toso, "Wind Turbine Fault Detection: A Semi-Supervised Learning Approach With Automatic Evolutionary Feature Selection," 2020 International Conference on Systems, Signals and Image Processing (IWSSIP), Niteroi, Brazil, 2020, pp. 323-328.
[5] Magda Ruiz,Luis E.Mujica,SantiagoAlférez et.al. Wind turbine fault detection and classification by means of image texture analysis[J].Mechanical Systems and Signal Processing Volume 107, July 2018, Pages 149-167.
[6] Z. Liu and L. Zhang, "Naturally Damaged Wind Turbine Blade Bearing Fault Detection Using Novel Iterative Nonlinear Filter and Morphological Analysis," in IEEE Transactions on Industrial Electronics, vol. 67, no. 10, pp. 8713-8722, Oct. 2020.