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A FAST PULSE SIGNAL DETECTION METHOD BASED ON THE MG-YOLOv11n NETWORK

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Abstract: This study presents MG-YOLOv11n, a lightweight adaptation of YOLOv11n for rapid detection of pulse signals in time–frequency representations. To improve discrimination between signals with closely related spectral patterns, the network incorporates a multiscale attention module that emphasizes informative regions and feature channels. Computational demands are reduced by substituting selected conventional convolutions with ghost convolutions and removing low-contribution channels through L1-regularization-guided structured pruning. The resulting network is fine-tuned to recover detection performance after compression. Experimental evaluation indicates that MG-YOLOv11n achieves high detection accuracy while requiring fewer model parameters and less computation, supporting efficient analysis of pulse signals.
Keywords: Pulse signal detection; MG-YOLOv11n; Multiscale attention mechanism

1 INTRODUCTION

Conventional pulse signal detection relies heavily on energy detection, correlation detection, and change point detection, which often struggle in complex electromagnetic environments. Recently, deep learning has been increasingly adopted to overcome these limitations [1-4]. Among various architectures, YOLO models have become the dominant single-stage detectors due to their efficient end-to-end processing [5-9]. Specifically, YOLOv11 introduces a more lightweight design that accelerates inference while preserving accuracy, making it highly attractive for real-time pulse analysis [10]. Nevertheless, the standard YOLOv11 still suffers from false alarms when distinguishing similar signals and missed detections for small targets. Moreover, its computational footprint often remains too heavy for strict real-time constraints in practical deployments.

2 MG-YOLOv11n NETWORK FOR PULSE SIGNAL DETECTION

The original YOLOv11n adopts a fixed feature fusion scheme, which does not distinguish the relative importance of different channels and spatial regions in time–frequency maps. This can make it difficult to identify signals with similar modulation patterns, particularly when weak pulses are present. In this study, a multiscale attention mechanism is added to the network. It combines features from multiple branches and uses channel and spatial attention to identify time–frequency patterns that are useful for distinguishing different pulse signals [11-12].

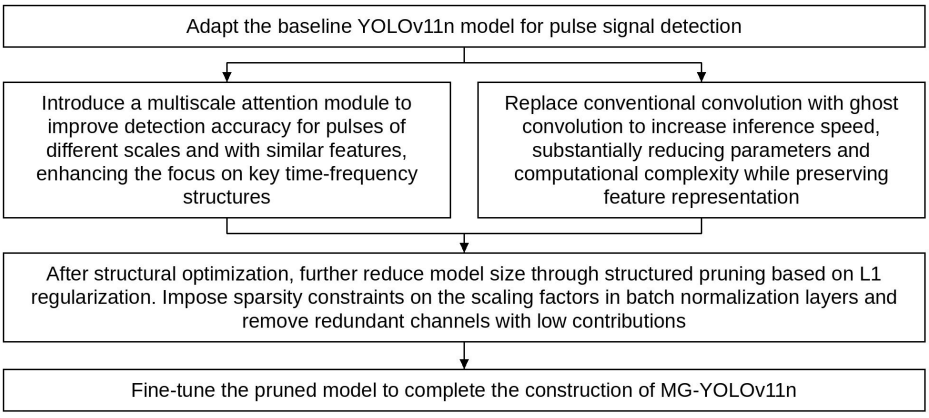


Figure 1 Improvements to the YOLOv11n Network

Another consideration is the computational cost of convolutional operations. Processing large numbers of time–frequency images requires repeated convolution, which increases the number of calculations. To reduce this cost, some standard convolutional layers are replaced by ghost convolution modules [13]. Rather than generating all feature maps through standard convolution, these modules produce a small set of feature maps first and then generate additional

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maps through simple linear operations. In this way, fewer parameters and calculations are needed, while the main features of the pulse signals are retained.

The model is also simplified through structured channel pruning. The scaling factors in batch normalization (BN) layers are used to estimate the importance of individual channels. L1 regularization is introduced during training to encourage smaller scaling factors for less important channels [14-15]. After training, channels with small scaling factors are removed, and the pruned model is fine-tuned to recover possible losses in detection accuracy [16]. These modifications form the MG-YOLOv11n model, whose structure is presented in Figure 1.

The training procedure for MG-YOLOv11n is shown in Figure 2.

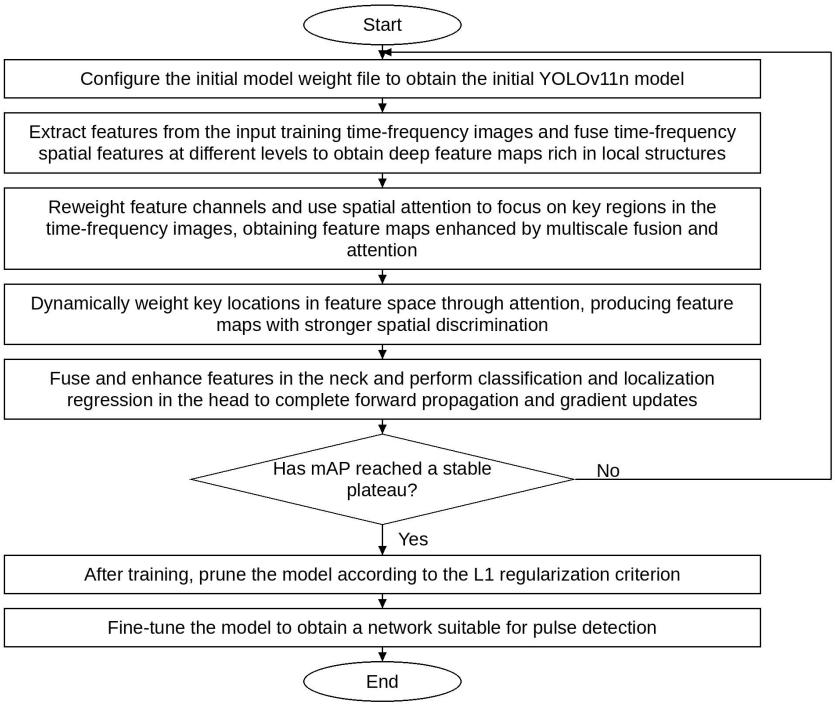


Figure 2 Training Procedure for the MG-YOLOv11n Network

3 EXPERIMENTAL ANALYSIS

Due to the scarcity of real-world pulse recordings, we constructed a hybrid dataset combining measured in-phase/quadrature (IQ) data with parametrically simulated signals. All waveforms were converted into time–frequency images via the short-time Fourier transform (STFT) [17]. The dataset covers eight representative modulation types (e.g., single-frequency, linear/sinusoidal/quadratic frequency-modulated, and polyphase-coded signals), with at least 3,000 samples per category and signal-to-noise ratios (SNRs) ranging from −5 to 10 dB. The data were randomly split into training, validation, and test sets in an 8:1:1 ratio.

To facilitate performance comparisons among different detection methods, commonly used object detection metrics are introduced: precision P, recall R, F1 score, and mean average precision (mAP).

Precision P is the proportion of correctly predicted positive bounding boxes among all bounding boxes predicted as positive by the model [18]. It is calculated as follows:

$$\mathrm{P} = \frac{TP}{TP+FP} \tag{1}$$

Here, TP denotes correctly predicted positive samples, for which both the predicted class must be correct and the intersection over union (IoU) between the predicted and ground-truth bounding boxes must reach the specified threshold. FP denotes incorrectly predicted positive samples, including localization errors, classification errors, and false detections of the background.

Recall R is the proportion of all actual positive samples that are successfully predicted by the model. It is calculated as follows:

$$\mathrm{R} = \frac{TP}{TP+FN} \tag{2}$$

Here, FN denotes actual targets that are not correctly detected by the model. This generally includes two cases: an existing target is not detected at all, or the confidence of a predicted bounding box fails to reach the specified threshold, resulting in a missed detection.

Mean average precision (mAP) is the principal comprehensive performance metric in object detection. By averaging the average precision (AP) across all classes, it reflects the overall capability of a model in multiclass detection tasks [18]. It is calculated as follows:

$$\mathrm{AP} = \int_0^1 p(r)dr\,,\ \mathrm{mAP} = \frac{1}{N_c}\sum_{i=1}^{N_c} \mathrm{AP}_i \tag{3}$$

Here, $p(r)$ denotes the precision–recall curve, and N_c denotes the number of target classes.
There are two main forms of mAP. mAP_{50} is the mean average precision calculated at an IoU threshold of 50%. $mAP_{50:95}$ is a stricter evaluation metric, obtained by calculating mAP at IoU thresholds sampled at fixed intervals from 50% to 95% and then taking the average. This metric provides a more comprehensive and accurate assessment of overall model performance across different IoU thresholds.
Table 1 compares MG-YOLOv11n with several established detection models. The proposed network obtains an mAP_{50} of 98.78% and an $mAP_{50:95}$ of 92.98%, with an inference time of 4.63 ms, 2.93 GFLOPs, and 2.42 million parameters. These measurements indicate a favorable combination of detection performance and model compactness within the reported experimental setting.

Table 1 Comparison Results of Different Models

Model	mAP50 (%)	mAP50:95 (%)	Processing time (ms)	FLOPs (G)	Parameters (M)
Faster R-CNN [19-20]	87.53	79.72	104.57	369.82	136.77
SSD [21-22]	84.36	78.58	18.64	64.15	24.15
RetinaNet [23-24]	87.76	78.67	21.18	97.14	37.68
G-YOLOv11 [25]	89.88	79.38	3.28	1.14	0.67
MG-YOLOv11n	98.78	92.98	4.63	2.93	2.42

4 CONCLUSIONS

We developed MG-YOLOv11n, a lightweight and efficient network tailored for real-time pulse signal detection in time–frequency images. By integrating a multiscale attention mechanism, the model significantly improves its ability to distinguish signals with highly similar spectral features. Furthermore, the incorporation of ghost convolutions and L1-regularization-based structured pruning effectively eliminates computational redundancy. Extensive experiments on a hybrid dataset confirm that MG-YOLOv11n successfully balances high detection accuracy with low computational overhead, making it a practical solution for real-time pulse analysis in resource-constrained environments.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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