УДК 004.93+623.6

DEVELOPMENT OF AN ENHANCED DEEP LEARNING METHOD SEARCH SYSTEMS FOR EXPLOSIVE DEVICES

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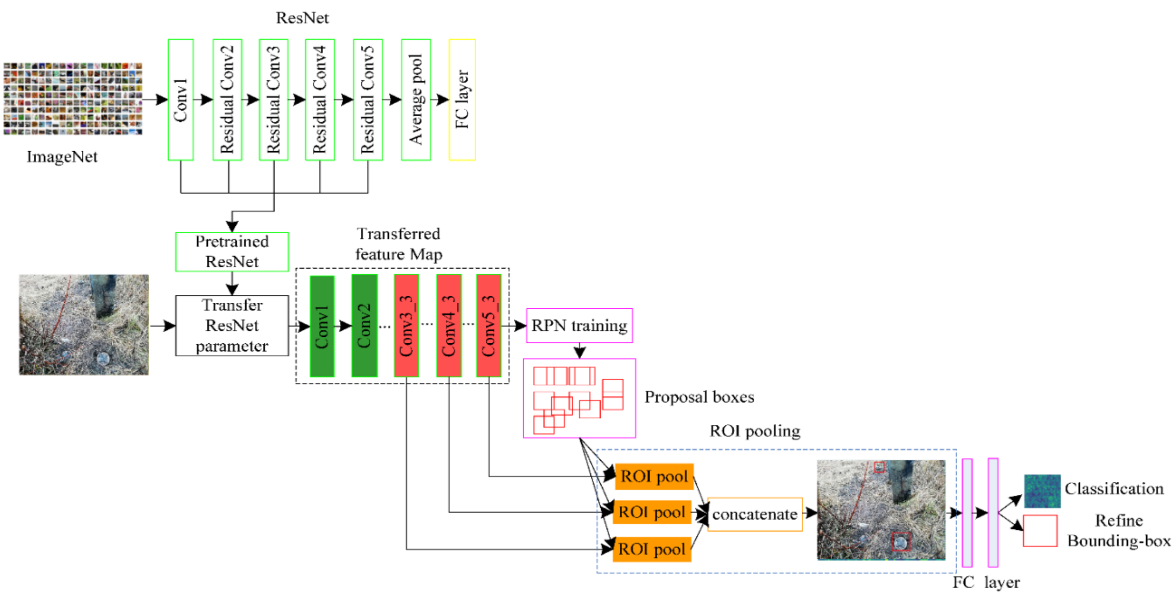
Keywords: learning algorithms, Faster Region-Based Convolutional Neural Network, landmine,region proposal network.

SAR's Faster R-CNN utilizes a region proposal network (RPN) to generate potential regions of interest (ROIs) directly from the input image, in contrast to Fast R-CNN, which relies on external sources for region proposals. The RPN consists of three convolutional layers and a newly introduced proposal layer, implemented as a user-defined function (UDF) in either Python or C++. The Python code that constructs the RPN is compatible with CNTK. The input to the RPN is the same convolutional feature map used as input to the ROI pooling layer. This feature map is fed into the initial convolutional layer of the RPN, with the output then propagated through the subsequent two convolutional layers. One of these layers predicts class scores for each candidate region, specifically for each anchor at every spatial position, resulting in a tensor of dimensions (9 anchors x 2 scores x width x height). These scores are then transformed via a SoftMax operation to yield objectness scores per candidate, indicating the likelihood of a candidate region containing a foreground object. The other convolutional layer predicts regression coefficients for adjusting the position of the ROI for each candidate, leading to a tensor of dimensions (9 anchors x 4 coefficients x width x height). This integration contributes to an improved Faster R-CNN, referred to as EFRCNN, as depicted in Picture



1.

Picture 1.Pipeline of landmine detection based on EFRCNN.

The proposal layer takes in the regression coefficients and objectness scores (representing foreground and background probabilities). Initially, it applies the regression coefficients to the generated anchors, constraining the results within the image boundaries and filtering out excessively small candidate regions. Subsequently, it arranges the candidates based on their foreground probability, employs non-maximum suppression (NMS) to reduce redundant candidates, and then samples the desired number of ROIs for its output.During training, Faster R-CNN introduces two additional layers: the anchor target layer and the proposal target layer. The anchor target layer generates target values for the objectness score and the RPN regression coefficients, which are utilized in the loss functions of the RPN. Similarly, the proposal target layer generates target class labels for the ROIs and regression coefficients per class for the final detector, used in the loss functions of the detector.For evaluation purposes, only the proposal layer is necessary since targets for loss functions are not required. The proposal layer is available in Python as well as C++ in CNTK, while the target layers are presently only accessible in Python. Consequently, training Faster R-CNN must currently be conducted through the Python API.

The proposed EFRCNN underwent evaluation on the test dataset and another set comprising high-resolution images (depicted in Picture 2). The training of EFRCNN necessitated approximately 1200 epochs. Furthermore, such an algorithm can be implemented (ported) onto the quadcopter from which the dataset was acquired using platforms like Raspberry Pi, as illustrated in Picture 3.

Picture 2.Faster R-CNN fined mine. Picture 3. Prototype of adrone used for high-resolution image capture

Conclusion

Enhancements to the original Faster R-CNN involve employing a technique that concatenates high-level and low-level features, enabling more effective detection of objects across various sizes. This modification leads to a significant enhancement in performance compared to traditional methods such as SVM and template matching, which are deemed insufficient for the current application.

List of literature:

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