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IMAGE SPLICING DETECTION - COMPARISON OF DMAC AND DMVN NETWORKS

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Abstract---Constrained image splicing detection and localization (CISDL) is a difficult task for image forensics that examines two input suspicious pictures and determines whether one contains suspected portions copied from the other. Here a unique adverse learning approach for training the deep matching network for CISDL is presented. The goal of the deep matching network based on atrous convolution (DMAC) is to create two high-quality candidate masks that show the suspicious regions of the two input pictures. The correlation layer based on the skip architecture is proposed to capture hierarchical features in DMAC, and Atrous spatial pyramid pooling is used to extract features with rich spatial information.Another model called DMVN uses the same process as DMAC but it is not use atrous convolution. Atlast a comparative study of both models was done ,in which the DMAC model is better because it gives high resolution fined grained mask.

Keywords:Atrousconvultion,DMAC,DMVN,CISDL

I. INTRODUCTION

Malicious image forgery is becoming a global epidemic in recent years, due to the rapidly declining cost of digital cameras and quick development of sophisticated image editing tools. Forgers may use forged images to produce fake news, spread rumors or give false testimony, which result in negative social impacts. Image forensics, which seeks to distinguish forged images and prevent forgers from using forged images for unscrupulous business or political purposes, has attracted great attention in research and industrial communities. A variety of image forensics methods investigate an individual image and detect its high-level or low-level inconsistencies caused by image manipulation. However, it is still a challenging task to accurately distinguish forged images, due to advanced image manipulation techniques and limited information provided by a single image. Moreover, these image forensics methods identify forged images or regions without providing the source of forged regions or specific tampering process, but these auxiliary evidences can provide more clues and make results more convincing in real applications. Constrained image splicing detection and localization (CISDL) is newly formulated in the Media Forensics Challenge. Different from “conventional” splicing detection, “constrained” means that the inputs are two images: one is a probe image and the other is a potential donor image. In CISDL given a probe image P and a potential donor image D, CISDL aims to detect if a region of D has been spliced into P, and consequently provide mask images Pm and Dm indicating the regions of P were spliced from D. DMVN generates correlation maps by comparing high-level low-resolution feature maps of VGG, and constructs an inception-based mask convolution module to locate suspected regions. However, low-resolution feature maps restrict DMVN's ability to detect accurate boundaries and small suspected regions. Here proposed a deep matching

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network based on atrous convolution (DMAC) to generate high-quality candidate masks from high-resolution feature maps.

The basic DMAC architecture achieves significant improvements over DMVN.

This work, proposes a DMAC network which takes two images as inputs.These input images are fed into a atrous convolution network for feature map extraction.The extracted feature maps fed into the correlation layer and atrous spatial pyramid pooling for feature maps comparisons.

Fig 1.a)Donor Image b)Donor Mask c)Probe Image d)Probe mask

II. LITERATURE SURVEY

In [1] Proposes a new convolutional layer that suppresses image content and learns forgery detection.In [1] they proposed a CNN to learn manipulation detection features directly from data and it is used in image forensicsIn [2] DMAC is combined with adversarial learning for effective image forgery detection.In [3] propose an optimized 3D lighting estimation method by incorporating a more general surface reflection model.In [4] propose a framework to improve the performance of forgery localization via integrating tampering possibility maps. In [5] proposed algorithm automatically computes a likelihood map indicating the probability for each 8 × 8 discrete cosine transform block of being doubly compressed.

III. PROPOSED METHODOLOGY

In this section, explains the proposed framework, as shown in fig 2. In the DMAC model there are three modules namely feature extraction module, correlation module and ASPP (Atrous Spatial Pyramid Pooling) . In the feature extraction module atrous convolution is adopted to enrich the spatial information of convolutional features.

In the correlation module ,the skip architecture is designed for hierarchical features comparisons and in the ASPP module is used to capture the information of different scales, Atrous Spatial Pyramid Pooling is constructed to generate the final mask. ASPP contains multiple parallel atrous convolutional layers with different sampling rates.

In DMAC Model,two images as inputs probe and donor.In which donor is the is the original image which is captured by camera also called as authentic image and probe image is the image containing spliced portion of donor image also called as tampered image.This two image is given as input to the model and it produce high resolution fine grained mask as output.The DMAC model is using atrous convolution which is used to give high resolution mask.Atlast creating another model called DMVN , in this which is not using atrous convolution and compare with DMAC model for accuracy.

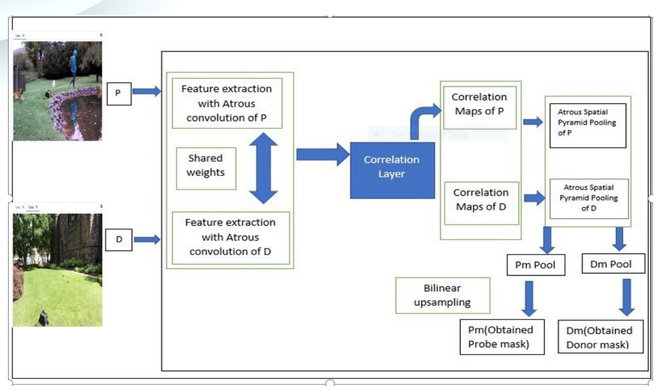

Fig 2.Proposed System Architecture

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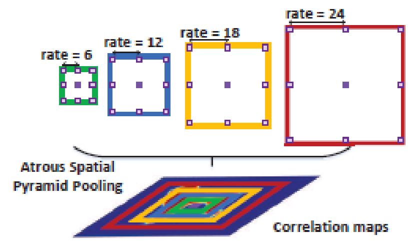
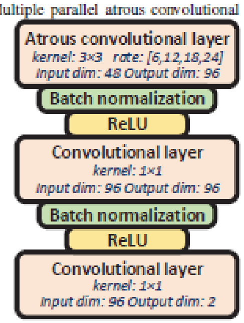
The DMAC network is an unique adversarial network in which feature extraction modules employing atrous convolution, the correlation layer with skip architecture, and ASPP are designed to enrich geographical information.In DMAC atrous convolution, the correlation layer and ASPP are used to capture hierarchical properties and localise impacted regions at many scales, respectively. The detection network and discriminative network, which act as losses with supplementary parameters, monitor DMAC's adversarial training.



(a) Multiple parallel atrous convolutional layers.



(b) The ASPP separate branch.

A. Feature Extraction with Atrous Convolution

CNNs' pooling or downsampling techniques necessarily degrade the spatial resolution of the output feature maps. As a result, in this research, atrous convolution is employed to create high-resolution feature maps. Atrous convolution allows us to vary the field-of-view of filters by adjusting the rate value without adding any more parameters.This module alters the image by adjusting the colour, contrast, and light intensity, which aids in the creation of a high-resolution mask.

Assume the input feature maps are scaled down by a factor of two before being convolved with standard convolution filters. The created feature maps are just a fourth the size of the original feature maps, and traditional filters only acquire answers from a quarter of the image locations. If we eliminate the downsampling layer and directly convolve the input feature maps, the filters will have a smaller field of vision. Fortunately, we may keep the original field-of-view by employing atrous convolution with rate r = 2. Using atrous convolution techniques, we can create high-resolution feature maps, get all answers from the input feature maps, and don't need any additional parameters or calculation.Despite the fact that the effective filter size increases, we only need to examine non-zero filter values, resulting in a constant number of filter parameters and operations per site.

B. Correlation Computation Module

To build dense high-resolution feature maps, atrous convolution is used as the basic process.One of the most difficult difficulties in deep matching tasks is deep feature comparison. For other tasks, only the neighbouring fields are compared, allowing for the creation of complex correlation layers. They usually compute the scalar product of a pair of individual descriptors at each place for long-range correlation computing tasks.We can denote correlation computation procedure as a function. The skip architecture is proposed to effectively organize the atrous convolution and hierarchical convolution features.It makes full use of the feature extraction module's wealth of information. Three sets of feature maps are produced by the atrous convolution layer: f3, f4, and f5. As a result, three sets of correlation feature maps can be created using the feature maps f3, f4, and f5, with no upsampling or mapping functions required.The computation procedure of the proposed correlation layer based on the skip architecture can be summarized as Algorithm: The skip architecture is used to compute the correlation layer.

C. Atrous Spatial Pyramid Pooling

The fact that the tampered portions are on different scales is a problem in the image splicing detection technique. The final masks are generated using Atrous Spatial Pyramid Pooling (ASPP), which captures the information

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on multiple scales provided by the correlation maps.Simply ASPP is a discriminative network that drives the DMAC network to produce masks that are hard to distinguish from ground truth ones. Multiple atrous convolutional layers with varying sampling rates are present in ASPP. As a result, those obscene convolution filters have varying field-of-views and can focus on altered parts of various scales. A separate branch of convolutional layers, batch normalisation, and ReLU layers follow each atrous convolutional layer with one sample rate.The individual branches are then merged to create the finished masks. During mask formation, there is no upsampling operation with learnable parameters, thus we just use bilinear upsampling during test time.

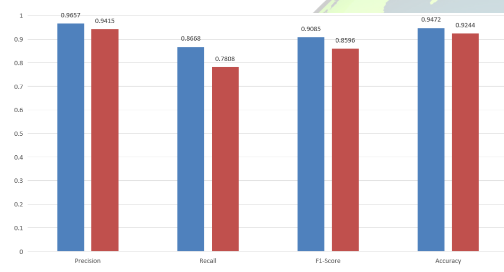

Fig 3: Atrous Spatial Pyramid Pooling [6]

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IV. RESULT AND DISCUSSION

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Precision: 0.8541114489666498
Recall: 0.9286295170072838
F1 Score: 0.8898130659054911
Accuracy: 0.9384002685546875
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Fig 4- Result of DMAC Model

Fig 5- Comparison Between DMAC and DMVN

V. CONCLUSION

This work provides a simple but effective framework for detecting image splices. A unique adversarial learning framework is proposed to deal with the CISDL task. To improve the DMAC network's ability to detect small matching regions and multi-scale regions, atrous convolution, the skip architecture, and ASPP are used.A lot of experiments are conducted on all generated datasets and also all publicly available datasets.The experimental results demonstrate the appealing performance of the proposed adversarial learning framework and the DMAC network.The use of atrous convolution and ASPP has clearly increased the effectiveness of the algorithm compared to the existing ones.Although the techniques to detect small tampered regions and regions under huge changes still need further research.

REFERENCES

[1] Belal Ahmed,T. Aaron Gulliver,Saif alZahir(2020) " image splicing detection using mask-RCNN", "Verlag London Ltd., part of Springer Nature 2020".

[2] Snigdha K. Mankar, Prof. Dr. Ajay A. Gurjar(2015) image splicing detection based on SVM(Support Vector Machines) classifier at IETE Amravati Center Volume 5.

[3] A. Alahmadi, M. Hussain, H. Aboalsamh, G. Muhammad, G. Bebis, and others, "Splicing image forgery detection based on DCT and Local Binary Pattern," in Global Conference on Signal and Information Processing (GlobalSIP), 2013 IEEE, pp. 253–256,2013.

[4] Hsu Y-F, Chang S-F.(2007). Image splicing detection using camera response function consistency and automatic segmentation.In:Multimedia and Expo, IEEE International Conference on, p. 28–31.

[5] Chi-Man Pun, Bo Liu, Xiao-Chen Yuan , "Multi scale noise estimation for image splicing forgery detection"in Journal of visual communication and image representation,pp.195-206,2016.

[6] Y. Liu, X. Zhu, X. Zhao and Y. Cao, "Adversarial Learning for Constrained Image Splicing Detection and Localization Based on Atrous Convolution," in IEEE Transactions on Information Forensics and Security, vol. 14, no. 10, pp. 2551-2566, Oct. 2019, doi: 10.1109/TIFS.2019.2902826.