Intro

Deep Learning Project

Image Forgery Detection

Group 32

Intro Overview

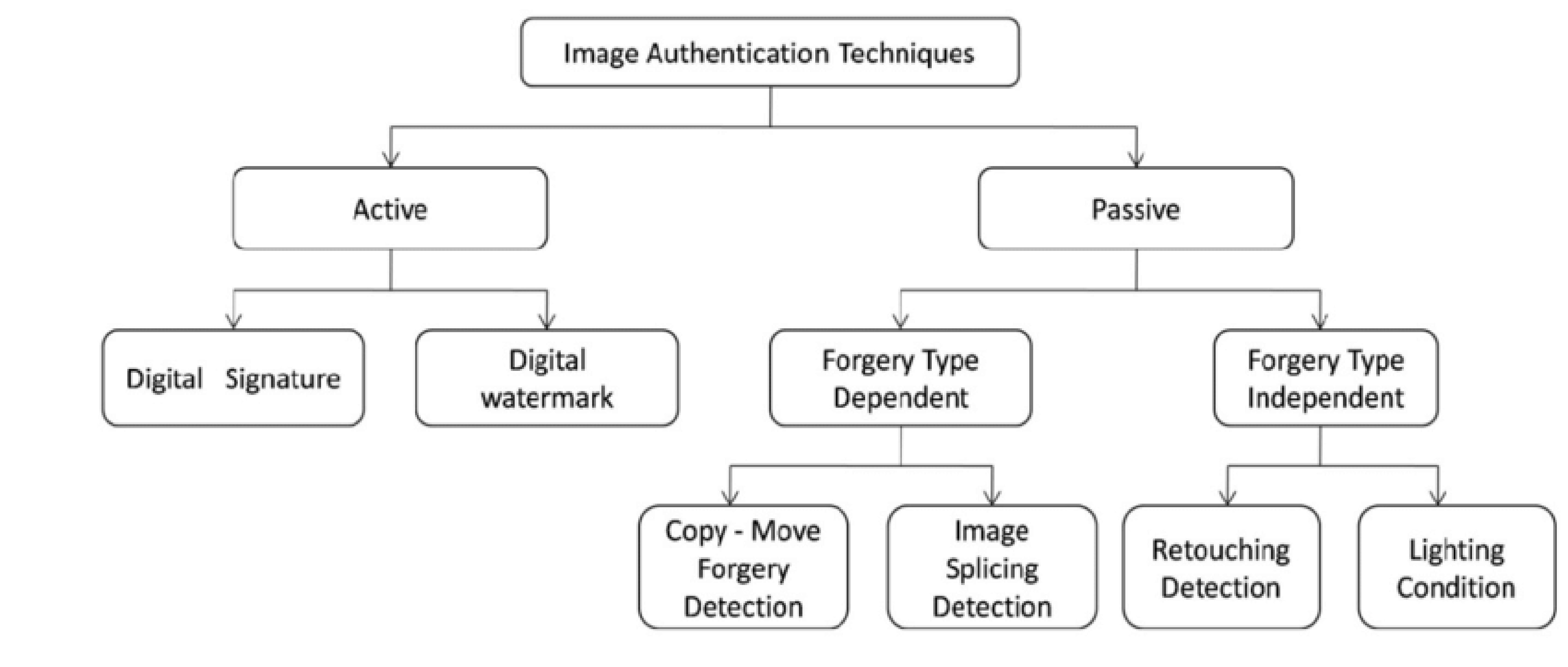
Image Forgery Detection using Deep Learning

Introduction

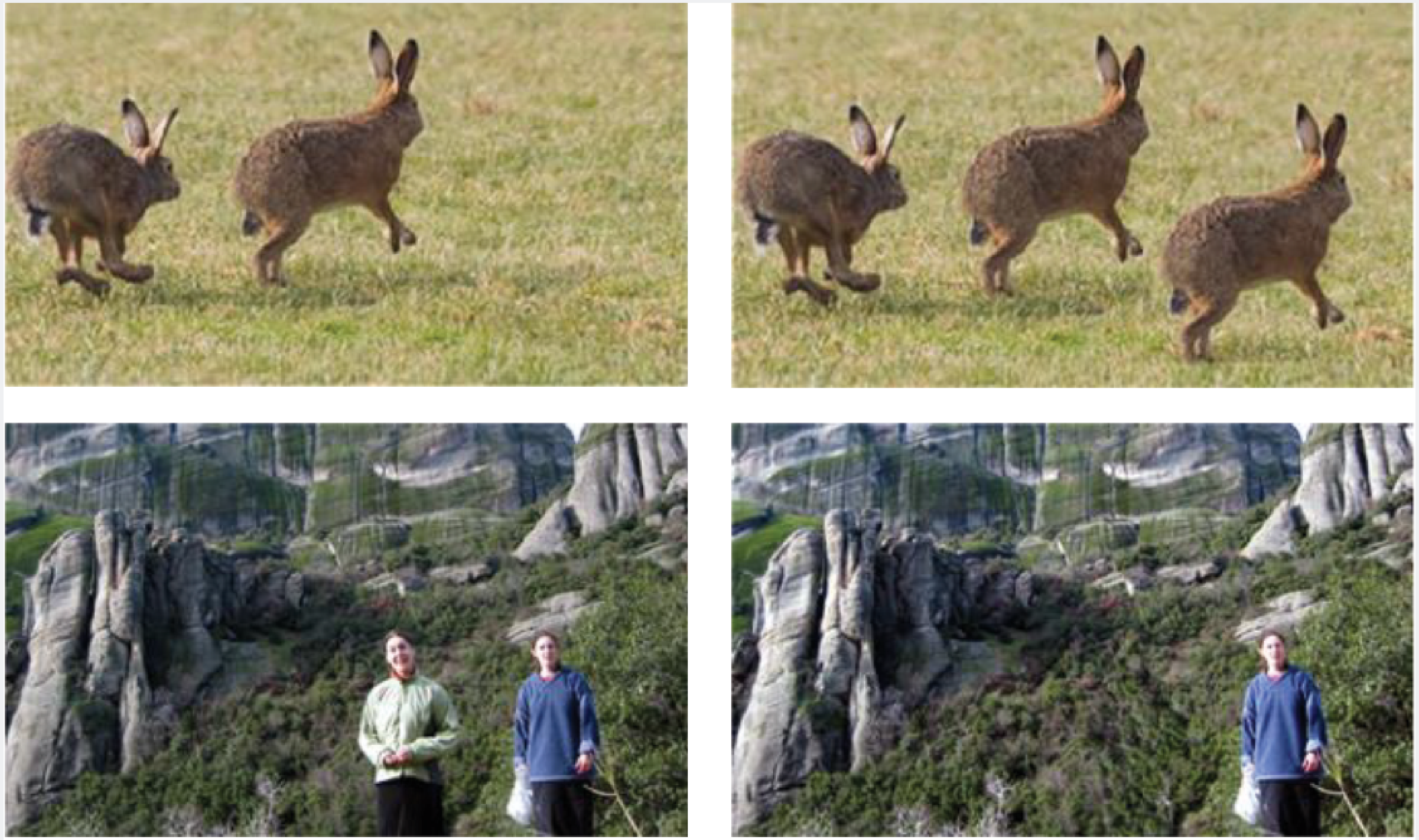
Copy-move and splicing are two prominent image forgery techniques that pose significant challenges in image forensics. Copy-move involves duplicating and inserting parts of an image into other areas, while splicing entails merging content from different images. Addressing these issues using deep learning requires the development of advanced algorithms capable of automatically detecting and localizing the manipulated regions. Accurate detection of copy-move and splicing is crucial for preserving the integrity of digital visual content, ensuring trustworthiness in various domains, including journalism, law enforcement, and social media verification.

Image Forgery Detection using Deep Learning

Types Of Image Forgeries



Copy Move



(a) The original images (b) The copy-move forged images

Splicing

(a) (b)

Objectives

We show that even without multi-level feature extraction using signal processing techniques, computer vision ap proaches leveraging CNNs can do significantly well in image forgery classification

We report that transfer learning is not suitable due to the differences in the target and the source domain.

We also demonstrate how filters with bigger size can be used instead of maxpooling layers to reduce computa tional cost.

Finally, we reveal that the normal image dataset without applying any transformation yielded superior performance.

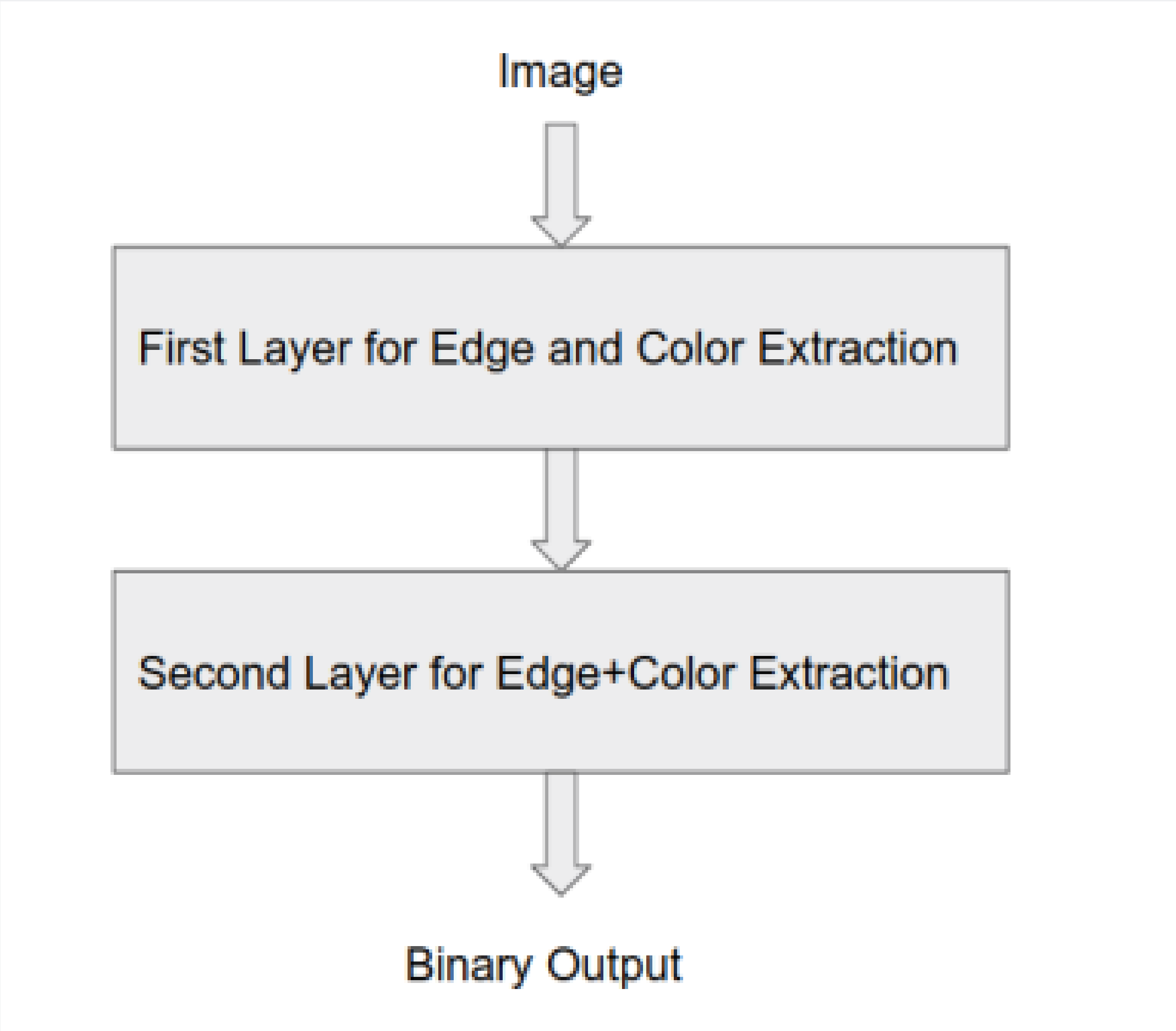
Image Forgery Detection using Deep Learning

Literature Survey

Method	Detected attacks	Localization	CASIA1 Acc.%	CASIA2 Acc.%	MICC-F220 Acc.%	**MICC-F600 Acc.%**	MICC-F2000 Acc.%	Other perf.
Agarwal and Verma [4]	Copy-move	Yes	–	–	99.11	–	–	55% FPR on MICC-F220
Abdalla et al. [1]	Copy-move	Yes + Source id.	–	–	–	–	–	88.35% F1-score on custom dataset
Wu et al. [105]	Copy-move	Yes + Source id.	–	76.65	–	–	–	75.98% F1-score on CASIA2
Elaskily et al. [25]	Copy-move	No	–	–	**100**	**100**	**99.7**	–
Ouyang et al. [78]	Copy-move	No	–	–	–	–	–	43% det. error on CMFD
Doegar et al. [22]	Copy-move	No	–	–	93.94	–	–	–
Cozzolino and Verdoliva [18]	Splicing Copy-move	Yes	–	–	–[a]	–	–	82.1% AUC on DS0-1 and 58.3% AUC on Korus
Zhang et al. [107]	Splicing Copy-move	Block-wise	91.09[b]	91.09[b]	–	–	–	–
Rajini [85]	Splicing Copy-move	Yes	–	**99.07**[c]	–	–	–	–
Marra et al. [69]	Splicing Copy-move	No	–	–	–	–	–	82.4% AUC on DS0-1 and 65.5% AUC on Korus
Rao and Ni [86]	Splicing Copy-move	No	**98.04**	97.83	–	–	–	96.38% acc. on DVMM
Majumder and Alim Al Islam [68]	Splicing Copy-move	No	–	79	–	–	–	–
Thakur and Rohilla [97]	Splicing Copy-move	No	–	–	–	–	–	95.97% acc. on CoMoFoD

Proposed method

A. Primary CNN Architecture



Proposed method

B. Knowledge Transfer from Pre-trained Models

Feature usage from another pre-trained model is another way to augment learning of a neural net model [4]. ImageNet is a popular image competition where a 1000- multiclass classification challenge is thrown to the world wide computer vision researchers. There are various models that perform very strong (top-5 error around 3- 5% only) such as VGG-16, VGG-19 [27], Resnet [28]. The idea is to leverage feature from internal layers of such models and train another layer connected on top of it. The new layer is fed the features. As a result, it learns to combine knowledge from both domains

C. Data augmentation

Data augmentation techniques are fairly common in CNN based models. We also apply real-time data augmentation during the training of our models. Mainly, shearing,zooming, vertical and horizontal flipping were applied.

Proposed method

D. Conversion from TIFF to JPG

CASIA v2.0 dataset contains images in tiff format. Since tiff format may represent both compressed and uncompressed images, the images with tiff format were con verted to JPG format. As a result, it may have resulted in double compression for many of the images in the dataset. Since we do not leverage manual feature engineering, we think it makes the problem more challenging

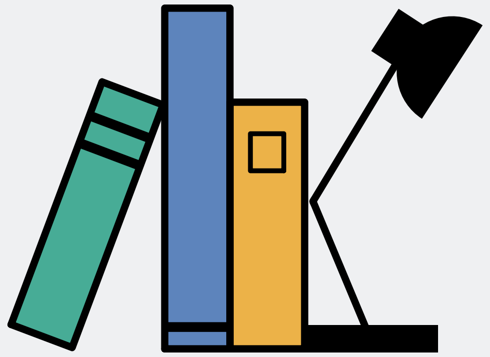
E. DCT and YCrCb transformation

As mentioned in Section II, we apply DCT and YCrCb transformations on our dataset separately. With three separate datasets (with no transformation, DCT transformation, and YCrCb transformation) we train our shallow CNN model three times separately.

Conclusion

1. The deep learning-based image forgery detection system successfully identifies copy-move and splicing manipulations, providing accurate and reliable results.
2. The integration of Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) enhances the system's ability to detect subtle and complex forgeries, ensuring robustness against various manipulation techniques.
3. This research significantly contributes to the advancement of image forensics, offering a valuable tool for maintaining the authenticity and credibility of digital visual content in diverse applications.

Image Forgery Detection using Deep Learning



Sources

01 https://ieeexplore.ieee.org/document/8631389

02 https://link.springer.com/content/pdf/10.1007/s11042-022-13797-w.pdf?pdf=button

Thank You

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