AutoSplice: A Text-prompt Manipulated Image Dataset for Media Forensics

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Abstract

Recent advancements in language-image models have led to the development of highly realistic images that can be generated from textual descriptions. However, the increased visual quality of these generated images poses a potential threat to the field of media forensics. This paper aims to investigate the level of challenge that language-image generation models pose to media forensics. To achieve this, we propose a new approach that leverages the DALL-E2 language-image model to automatically generate and splice masked regions guided by a text prompt. To ensure the creation of realistic manipulations, we have designed an annotation platform with human checking to verify reasonable text prompts. This approach has resulted in the creation of a new image dataset called AutoSplice, *containing 5,894 manipulated and authentic images. Specifically, we have generated a total of 3,621 images by locally or globally manipulating real-world image-caption pairs, which we believe will provide a valuable resource for developing generalized detection methods in this area [1]. The dataset is evaluated under two media forensic tasks: forgery detection and localization. Our extensive experiments show that most media forensic models struggle to detect the AutoSplice dataset as an unseen manipulation. However, when fine-tuned models are used, they exhibit improved performance in both tasks.*

1. Introduction

The proliferation of digital media and AI technology have made it easier to manipulate and fabricate digital content. In recent years, the rapid development of powerful deep generative models, such as Variational Autoencoders (VAEs) [14, 35], Generative Adversarial Networks (GAN) [32, 33], diffusion-based models [16, 56], and the latest large-scale language-image (LLI) models [22, 53–55, 73], have brought new challenges to the authentication of digital media. The generated images have become increas-

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[1] The AutoSplice dataset is available from https://github.com/shanface33/AutoSplice_Dataset
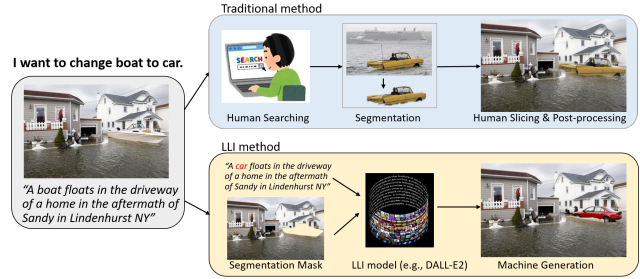

Figure 1. Comparison of our text-prompt-based image manipulation pipeline and traditional manual pipeline.

ingly realistic and convincing so that it can be difficult for human eyes to discern as artificial [59, 67].

Many efforts [29, 63, 66, 67] have investigated the challenges of GAN-generated images to media forensics due to the surge of GAN generation models, such as ProGAN [30], BigGAN [3], StyleGAN [32], etc. In addition, synthetic images from diffusion models can be identified with high accuracy using similar diffusion models in training, as demonstrated by [9]. The majority of previous studies have focused on entire synthesis using generative models. However, with the emergence of large-scale language-image models, local image manipulations guided by text prompts have become more accessible. Local manipulation of image regions, regardless of size, tends to be more realistic and challenging to detect than entire synthesis. In contrast to local manipulation techniques such as manual copy-move, slicing, or inpainting as described in [64], the latest language and vision models such as DALL-E [53, 54] allow for fully automatic and realistic local edits to images guided by a text prompt while preserving semantic information and stylistic elements, as shown in Figure 1. These models offer improved generation efficiency, image quality, and content flexibility compared to traditional local manipulation methods, and potentially revolutionize image manipulation.

A key question we investigate in this paper is: how much threat does the state-of-the-art language-image model pose to the current media forensic techniques? To explore this question, we first create a novel text-prompt manipulated

image dataset using DALL-E2 [2]. To create high-quality manipulations, we designed a semi-automatic annotation platform with manual checking. To ensure a diverse set of real-world media data, we utilized caption-image pairs from the Visual News dataset [43] as source data. Using automatic media analysis tools and human annotations, we extracted potential object regions to be manipulated from the images and parsed and replaced the corresponding text prompts in the captions. These captions were then taken as input to the DALL-E2 model for local image manipulation. For each caption-image pair input, we generated manipulated images (three by DALL-E2) and the corresponding manipulation mask. After data cleaning, our AutoSplice dataset contains 3,621 manipulated images and 2,273 authentic images.

Our dataset has several advantages over existing relevant media forensics datasets or methods, including high flexibility in content generation, high diversity in manipulation region, and good and reasonable generation quality. We use the large-scale language-image model, DALL-E2, for automatic local manipulation to create realistic forgery images, unlike previous local image manipulation methods based on manual and random object copy-move, slicing, or inpainting. Additionally, we only partially manipulate the image guided by the input region mask instead of generating the entire image, unlike recent semantic editing tools that use diffusion-based LLI models such as DiffEdit [10], Prompt-to-prompt [25], and Imagic [34]. Thanks to the powerful DALL-E2 generation model and human annotations, our dataset contains highly diverse and realistic synthesized images. We evaluate two media forensics tasks, namely, image forgery detection and image manipulation localization, on the AutoSplice dataset with lossless and lossy compression. Results show that pre-trained methods have limited generalization ability and unreliable prediction in detecting AutoSplice images. Models with fine-tuning on the dataset achieve improved performance, but also show vulnerability to compression.

2. Related Work

2.1. LLI Synthesis Models

Recent advancements in attention-based transformer and diffusion models have significantly improved text-to-image generation in the past two years. Several large-scale language-image models have been developed. The DALL-E model [54], proposed by OpenAI in 2021, uses an autoregressive transformer to achieve high-quality image generation on the MS-COCO dataset [40] without using any training labels. Other models, such as CogView [17], Parti [70], and Make-A-Scene [22], have also trained autoregressive transformer models on text and image tokens for text-to-image generation. In 2022, an updated version of DALL-E,

DALL-E2 [53], was developed using a diffusion model with CLIP image embeddings, making it computationally more efficient and able to produce higher-quality and more diverse samples. Other models, such as GLIDE [50], Stable-Diffusion [55], and Imagen [57], have also used diffusion models to improve text-to-image synthesis. Inspired by these powerful LLI synthesis models, several studies have developed text-guided image editing models, including DiffEdit [10], Prompt-to-prompt [25], Null-text Inversion [47], Imagic [34], and Muse [5]. These models apply local semantic editing to an image given a text input (with the desired edit) and an optional scene layout (segmentation map). However, their optimization tends to maximize the similarity to the original image while maintaining the ability to perform meaningful editing on local regions. This kind of entire synthesis can be easily identified if seen in training data [9]. To create more challenging fake media, we utilize the DALL-E2 model with high-quality local image editing techniques, which can generate text-guided pixels only in erased image regions.

2.2. Image Forensic Datasets

Two types of fake media datasets are relevant to our work: AI-synthesized image datasets and local image manipulation datasets. Several large-scale AI-synthesized image datasets have been collected from various GAN and VAE models, including DFFD [13] with GAN-based face attribute manipulations and entire face synthesis, CNNDetection [66] created using 11 CNN-based image generators, DF^3 [28] with entire face generation from six generation models (i.e., StyleGAN2 [33], StyleGAN3 [31], 3DGAN [4], Taming Transformers [20], LSGM [62], and Stable Diffusion [55]), and DMimageDetection [9] with diverse images from different GAN and diffusion models. The recent diffusion-based generation models are a class of likelihood-based models [51], which perturb data through successive addition of Gaussian noise and learn to recover the data by reversing this noising process. Although diffusion-based models achieve superior generation quality to GAN models [48, 60], a study [9] showed that current GAN image detectors can achieve near-perfect detection on similar diffusion models when trained with images generated with the diffusion models.

For local image manipulation, current research primarily focuses on techniques such as image slicing and copy-move. These methods involve copying and pasting specific regions of an image onto another part of the same image or a different one. Several widely used datasets, including Columbia [26, 49], CASIA [19], NIST16 [1], Coverage [68], Realistic Tampering [37], and IMD2020 [52], offer various types of locally manipulated images that are created either by manual operations or random slicing. However, these datasets have certain limitations, such as small

Table 1. Summary of previous image manipulation datasets and our work.

Dataset	Year	# Forged Image	# Authentic Image	Image Size	Format	Manipulation Method
Columbia [49]	2004	912	933	128×128	BMP	Random
Columbia [26]	2006	180	183	757×568 - 1152×768	TIF	Random
NIST16 [1]	2016	564	875	500×500 - 5616×3744	JPEG	Manual
CASIA v1 [19]	2013	921	800	374×256	JPEG	Manual
CASIA v2 [19]	2013	5,123	7,200	320×240 - 800×600	JPEG, BMP, TIF	Manual
Coverage [68]	2016	100	100	$400 \times 486^*$	TIF	Manual
Realistic Tampering [37]	2016	220	220	1920×1080	TIF	Manual
IMD2020 [52]	2020	2,010	414	$1062 \times 866^*$	JPEG, PNG	Collected from Internet
AutoSplice (ours)	**2023**	**3,621**	**2,273**	**256×256 - 4232×4232**	**JPEG**	**LLI model**

* Using the average image size.

data size (e.g., Columbia, Coverage, and NIST16), low authenticity level (e.g., Columbia's random region copy-move), or low flexibility and efficiency in generation due to careful and manual operations (e.g., CASIA and Realistic Tampering).

Recent advances in large-scale language-image models have demonstrated remarkable abilities in text-guided image manipulation and generation. Leveraging the power of these models, we introduce AutoSplice, a text-prompt guided image manipulation dataset that is built using the DALL-E2 model for automatic image editing. Table 1 provides further details regarding the existing image local manipulation datasets and our AutoSplice dataset.

2.3. Image Forgery Detection

The advancement of image forgery detection methods is a critical step in identifying manipulated/synthetic images for media forensics. Deep learning techniques have become increasingly popular for designing effective image forgery detectors. Most approaches consider forgery detection as a binary classification task and utilize well-designed deep neural networks to learn discriminative features automatically. Studies in this area can be divided into two categories: image-level forgery detection and pixel-level forgery detection (i.e., localization).

The former category concentrates on extracting global artifacts that synthesis models leave on the entire image, such as using augmented CNN models [66], frequency analysis [21], and re-synthesis residuals [24]. To improve the generalization ability for local image manipulation detection, recent studies [15, 28, 29, 41, 74] demonstrate the effectiveness of fusing local and global features in detecting different types of image forgery.

For manipulation localization, which aims to identify modifed image regions at the pixel level, existing methods mainly focus on identifying image tampering involving copy-move, splicing, removal, and faceswap. A subset of techniques formulates this task as a local anomaly detection problem and designs methods for capturing anomalies [6, 11, 69]. Several methods [2, 38, 39, 42, 45] uti-lize compression artifacts for forgery detection considering that the manipulation often involves double or more times of compressions. In addition, a branch of methods explores distinctive noise patterns in forged images, such as the RGB-N model [71] fusing RGB image content and image noise features, Noiseprint model with Siamese Network [12], [36], and ViT-VAE [6] to combine Noiseprint, High-pass filtering residuals, and Laplacian edge maps using Vision Transformer (ViT).

Given that the latest LLI models offer a powerful tool for realistic image generation and manipulation, presenting a potential threat of their misuse for spreading disinformation, our goal is to investigate the performance of current detectors on the newly created synthetic images. We will also pay particular attention to the detectors' ability in challenging social-network scenarios with image resizing and compression.

3. AutoSplice Dataset

To evaluate the difficulty of detecting media generated by recent LLI models using current forensic techniques, we introduce a new dataset called AutoSplice. In this section, we provide a comprehensive overview of the AutoSplice dataset creation process. The entire generation pipeline is illustrated in Figure 2. We begin by outlining the data pre-processing techniques and human annotation process. Next, we describe the data cleaning process, followed by a summary of the dataset and an analysis of its statistics.

3.1. DALL-E2

DALL-E2 [53] is a generative model that uses multiple modes to create synthetic images based on given text inputs. The model utilizes diffusion models to produce images based on CLIP image embeddings. Unlike traditional image synthesis approaches, DALL-E2 can also perform image inpainting by using both the input text and a region mask.
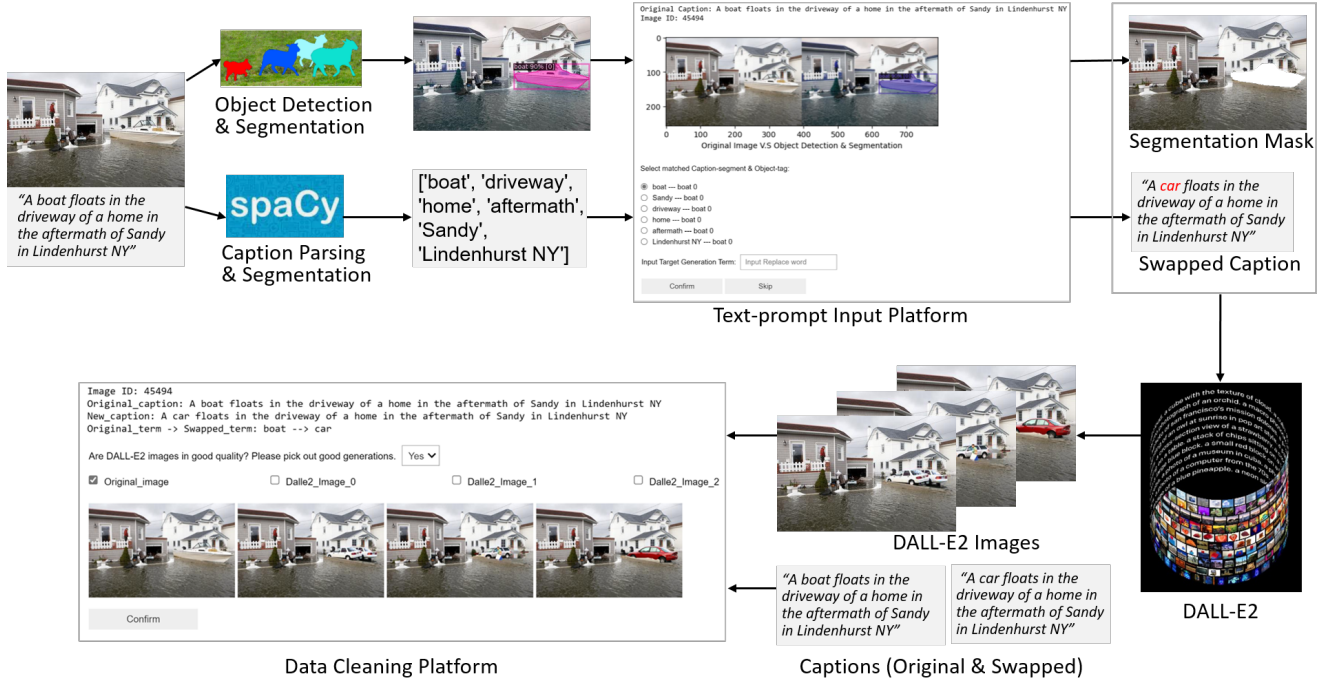
Figure 2. Pipeline of our text-prompt-based manipulation and annotation.

3.2. Dataset Construction

In this section, we introduce the details of the construction of the AutoSplice dataset.

3.2.1 Pre-processing

The pre-processing step for the DALL-E2 model involves providing a manipulation mask and a contextual text description to perform local image editing. In order to generate realistic manipulations, we propose using a specific object region with a modified caption where the corresponding text-prompt to the object is replaced with a target generation term. To achieve this, we use an object detection model to extract a list of object regions and a text parsing tool to segment text terms. We compare these terms with corresponding object-term pairs to facilitate further replacement and manipulation. Specifically, we use the Visual News dataset [43], which contains over one million news images along with their corresponding captions and metadata obtained from reputable real-world news sources (The Guardian, BBC, USA TODAY, and The Washington Post). This dataset has been utilized for various media forensic tasks, including the media manipulation detection [58] and text-image inconsistency detection [27]. For each sample in Visual News, we utilize the Detic model [72] to extract and segment object regions with detected object tags in the image. We also use spaCy ³ for sentence segmentation and noun term extraction, as shown in Figure 2. Human anno-

³ https://github.com/explosion/spaCy.

tations are then used to select the object with corresponding descriptions in the caption, and input target terms to replace the object description in the caption.

3.2.2 Human Annotations

Five annotators who are graduate and undergraduate students with professional backgrounds and have a clear understanding of the data annotation task for DALL-E2 input, strictly follow the steps outlined in Figure 2 during the data annotation process.

1. Select the matching object region tag in the real-world image and the corresponding text description term in the caption (if present).
2. Provide a target generation term that is similar but inconsistent with the original term and image.
3. Ensure that the modified caption has the correct syntax.

For each caption-image sample with a matched object-term pair, human annotations provide the two required inputs for the DALL-E2 model to perform local image generation: the segmented object region as the erased manipulation mask and the modified caption as the text prompt. The DALL-E2 model returns a group of three manipulation outputs for each generation.

3.2.3 Post-processing

To address the limitations of the DALL-E2 model in generating human, text, and abstract concepts [57], we conducted manual data cleaning to filter out images with visible visual

artifacts or caption-image pairs with undesirable consistencies. Given an original image-caption pair with the swapped caption and three DALL-E2 generated images, annotators were required to assess the visual quality of each generated image and identify images with good quality (i.e., no obvious artifacts). Since the definition of "good quality" is subjective and may vary among different annotators, each image was assessed multiple times by different annotators. We only retained images that received consistent labels from at least three annotators.

The high-quality DALL-E2 images were resized to match the dimensions of their corresponding authentic images. Despite being initially in PNG format, we compressed the generated DALL-E2 images using JPEG for two reasons. Firstly, their corresponding authentic images included in our dataset are in JPEG format. It is essential to eliminate format-level clues in the binary image forgery classification task. Secondly, JPEG is the most important and widely used image compression format [61], particularly on social media and websites, due to its simplicity and efficiency. Therefore, we chose both lossless (with a JPEG quality factor of 100) and gently lossy compression (with a quality factor of 90) formats to produce two variations of our DALL-E2 dataset.

3.3. Dataset Summary

Our AutoSplice dataset includes $3,621$ high-quality manipulated images and $2,273$ authentic images for each compression version. The data has been cleaned, and manipulation masks have been applied, allowing for further evaluation in both image forgery detection and image manipulation localization tasks. Figure 3 presents statistical information about the size of the manipulation region within the dataset, indicating that the dataset has a high diversity in the manipulation region. We further show some image examples in Figure 4.

4. Experimental Evaluation

This section outlines the evaluation experiments conducted on the AutoSplice dataset using state-of-the-art image-level and pixel-level forgery detection methods. The first experiment examines the generalization ability of existing pre-trained detectors to the LLI model manipulated images. Following this, we analyze the performance limits of these detectors in in-domain testing scenarios, where the models are fine-tuned on our AutoSplice dataset for both detection and localization tasks.

4.1. Evaluation Baselines

We evaluated five image forgery detection methods on our dataset: CNN-aug [66], ResNet50 Nodown [23], BeyondtheSpectrum [24], PSM [29], and GLFF [28]. These
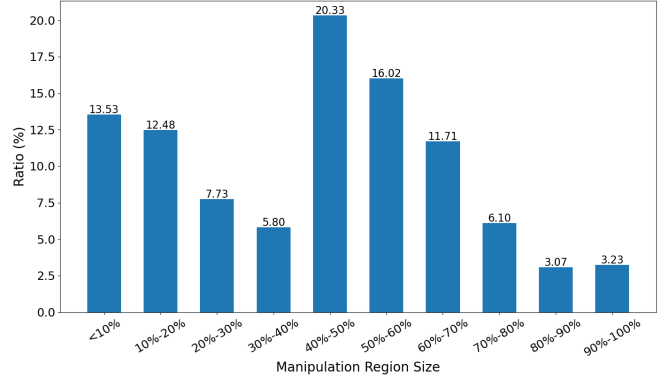

Figure 3. Statistical distribution of AutoSplice dataset in manipulation region size.

Figure 4. Examples in our AutoSplice dataset. The first column shows authentic images, while the second column displays forged images. The third column shows forgery masks.

models were chosen because they have demonstrated excellent performance in detecting image forgery, have been evaluated on both globally and locally manipulated images, and provide open-source codes and pre-trained models.

For pixel-level forgery detection and localization, we evaluated seven techniques that employ different feature learning strategies: Noiseprint [12], ManTra-Net [69], ForensicsGraph [46], CAT-Net [39], MVSS-Net [7], PSCC-Net [44], and ViT-VAE [6]. Table 2 presents detailed information on the feature design, training set, and software codes of these baseline methods.

4.2. Evaluation Metrics

To detect binary image forgery, we assign Positive (1) to the tampered image/pixel and Negative (0) to the authentic image/pixel. In image-level detection, we use standard metrics such as Area Under ROC Curve (AUC), True Positive

Table 2. Image forgery detection and localization baselines

Reference	Year	Feature	Training set	Software Code
CNN-aug [66]	2020	Augmented CNN features	ProGAN [66] (720K images)	https://github.com/PeterWang512/CNNDetection
ResNet50 Nodown [23]	2021	No down-sampling CNN features	ProGAN [66] (720K images)	https://github.com/grip-unina/GANimageDetection
Beyondthe-Spectrum [24]	2021	Re-synthesis residuals	ProGAN [66] (720K images)	https://github.com/SSAW14/BeyondtheSpectrum
PSM [29]	2022	Global & local features	ProGAN [66] (720K images)	https://github.com/littlejuyan/FusingGlobalandLocal
GLFF [28]	2022	Multi-scale features	ProGAN [66] (720K images)	https://github.com/littlejuyan/GLFF
Noiseprint [12]	2019	Noise residuals	4 datasets with 125 cameras	https://grip-unina.github.io/noiseprint/
ManTra-Net [69]	2019	Anomalous features	4 synthetic datasets	https://github.com/ISICV/ManTraNet
ForensicsGraph [46]	2020	Similarity graph	4 million image patches from 80 cameras	https://gitlab.com/omayer/forensic-graph
CAT-Net [39]	2021	Compression artifacts	4 synthetic datasets (960K images)	https://github.com/mjkwon2021/CAT-Net
MVSS-Net [7]	2021	Multi-view features	1 dataset (CASIA v2)	https://github.com/dong03/MVSS-Net
PSCC-Net [44]	2022	Spatio-channel correlation	0.38 million images	https://github.com/proteus1991/PSCC-Net
ViT-VAE [6]	2023	Multi-modal features	−*	https://github.com/media-sec-lab/ViT-VAE

* Using run-time training where the ViT-VAE model requires an independent training phase for each test image.

Rate (TPR), and False Positive Rate (FPR). For pixel-level detection, we calculate F1 score, Intersection over Union (IoU), precision, and accuracy (ACC) by comparing the results with the binary ground-truth mask using a fixed threshold of 0.5, as done in previous studies [6–8, 18, 65]. The average scores for all testing images are reported.

Experiment Settings. To evaluate our dataset, we adhered to the parameter settings used in the baseline implementation for each task. During the fine-tuning process, we set a 6:4 split between training and testing data to ensure that there was no overlapping between the two sets.

4.3. Comparisons on Image Forgery Detection

4.3.1 Pre-trained Models

We started by using five pre-trained models for image forgery detection and tested their ability to identify the AutoSplice forgery. The results, including AUC, TPR, and FPR, are presented in Table 3. Our analysis shows that all models trained on the ProGAN dataset [66], which includes 720K images (360K real images and 360K fake images across 20 object categories), experienced a performance decrease in detecting image forgery in the AutoSplice dataset. Only the ResNet Nodown [23] model achieved the best AUC on two compression sets. All other models had an AUC lower than 0.600. The low TPR and FPR scores suggest that most LLI model forged images were incorrectly classified as authentic, whereas authentic images were correctly identified. Additionally, all models performed poorly on JPEG-90 images with mild compression, indicating that the compression process reduces the distinguishability of features.

4.3.2 Fine-tuned Models

We fine-tuned four models with training codes on the AutoSplice training dataset, after considering that data-driven classification methods tend to perform better when the domain discrepancy is alleviated [44]. To ensure that compression artifacts did not influence the binary forgery detection task, we compressed the original images produced

by the DALL-E2 model using the same JPEG compression quality factor (75 [4]) as the authentic images derived from Visual News dataset [43]. We evaluated the detection performance on two testing subsets (JPEG-100 and JPEG-90) and reported the results in Table 4. As expected, most methods showed a significant improvement in the detection AUC and TPR when evaluated in the in-domain testing scenario. The CNN-aug [66] achieved the best performance on both compression sets. However, after fine-tuning, most methods had a significant increase in FPR, indicating that a greater number of authentic images were incorrectly classified.

Table 3. Image forgery detection results on AutoSplice dataset using pre-trained models. Best results are shown in bold.

Method	JPEG - 100			JPEG - 90		
	AUC↑	TPR↑	FPR↓	AUC↑	TPR↑	FPR↓
CNN-aug [66]	0.597	0.025	0.004	0.551	0.004	0.004
ResNet50 Nodown [23]	**0.750**	0.070	**0.002**	**0.664**	0.004	**0.002**
Beyondthe-Spectrum [24]	0.547	**0.335**	0.290	0.503	**0.303**	0.290
PSM [29]	0.586	0.038	**0.002**	0.535	0.005	**0.002**
GLFF [28]	0.572	0.055	0.013	0.526	0.016	0.013

Table 4. Image forgery detection results on AutoSplice dataset using fine-tuned models. Best results are shown in bold.

Method	JPEG - 100			JPEG - 90		
	AUC↑	TPR↑	FPR↓	AUC↑	TPR↑	FPR↓
CNN-aug [66]	**0.979**	**0.981**	0.372	**0.948**	**0.932**	0.372
Beyondthe-Spectrum [24]	0.797	0.785	0.341	0.787	0.762	0.341
PSM [29]	0.880	0.847	0.257	0.882	0.841	0.257
GLFF [28]	0.926	0.776	**0.077**	0.908	0.735	**0.077**

4.4. Comparisons on Image Forgery Localization

4.4.1 Pre-trained Models

We evaluated seven baselines for image forgery localization, and reported their pixel-level metrics in Table 5. Re-

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[4]The JPEG-75 compressed images are included in our AutoSplice dataset along with JPEG-100 and JPEG-90 versions at https://github.com/shanface33/AutoSplice_Dataset.

Table 5. Image forgery localization results on AutoSplice dataset using pre-trained models. Best results are shown in bold.

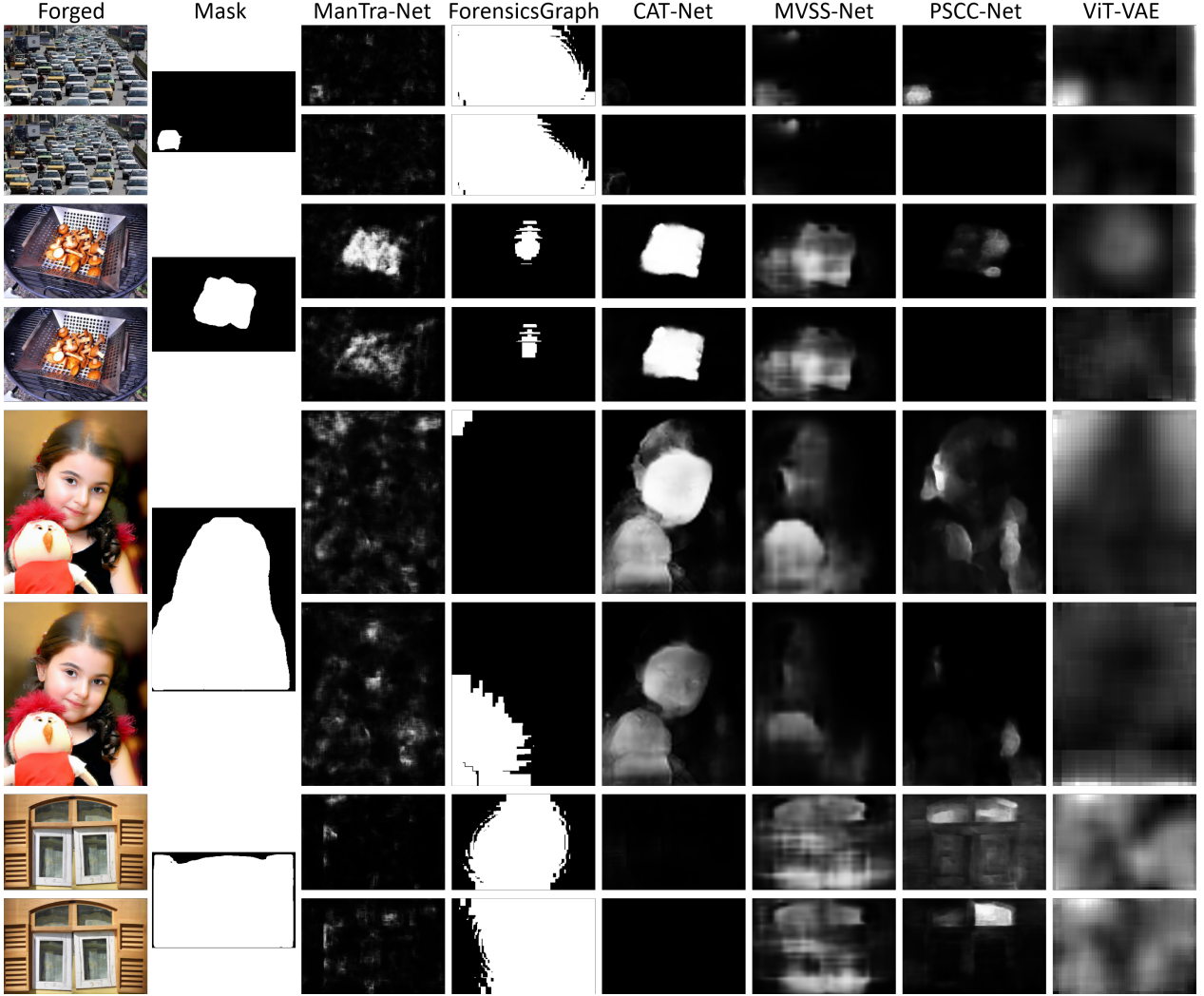| Method	Forged JPEG-100				Forged JPEG-90				Authentic
	F1↑	IoU↑	Precision↑	ACC↑	F1↑	IoU↑	Precision↑	ACC↑	ACC↑
Noiseprint [12]	0.333	0.217	0.390	0.480	0.316	0.205	0.373	0.467	0.594
ManTra-Net [69]	0.179	0.120	0.639	0.586	0.062	0.035	0.586	0.716	0.992
ForensicsGraph [46]	0.362	0.289	0.393	0.530	0.354	0.253	0.438	0.518	0.584
CAT-Net [39]	**0.751**	**0.648**	0.884	**0.827**	**0.676**	**0.579**	**0.833**	**0.793**	0.933
MVSS-Net [7]	0.330	0.238	0.734	0.677	0.141	0.093	0.516	0.612	0.991
PSCC-Net [44]	0.558	0.447	**0.899**	0.725	0.056	0.036	0.295	0.591	**0.998**
ViT-VAE [6]	0.156	0.115	0.245	0.560	0.244	0.183	0.275	0.534	0.835

Figure 5. Localization results of pre-trained models in detecting AutoSplice forged images with different manipulation regions. The images in odd rows are compressed using JPEG-100, while the images in even rows are compressed using JPEG-90.

sults varied significantly across models due to their different training data and forensics cues (detailed in Table 2). The CAT-Net [39] model performed the best thanks to its two-stream network that learns compression artifacts from both RGB and DCT domains, as well as its extensive and diverse training data. The PSCC-Net [44] also outperformed other methods on the JPEG-100 testing set, but its performance degraded significantly on the JPEG-90 set. Most models showed poor generalization ability on the AutoSplice dataset, with F1 and IoU lower than 0.37 and 0.29, respectively. For authentic images, where every pixel in the ground truth mask is negative, F1, IoU, and Precision met-

Table 6. Image forgery localization results on AutoSplice dataset using fine-tuned models. Best results are shown in bold.

Method	JPEG - 100				JPEG - 90				Authentic
	F1↑	IoU↑	Precision↑	ACC↑	F1↑	IoU↑	Precision↑	ACC↑	ACC↑
CAT-Net [39]	0.762	0.658	**0.882**	0.837	0.693	0.594	**0.844**	0.805	0.927
PSCC-Net [44]	**0.862**	**0.794**	0.847	**0.919**	**0.771**	**0.693**	0.775	**0.886**	**0.993**

rics are not appropriate. We reported the ACC in Table 5, and most methods achieved high accuracy in detecting authentic images derived from real-world media data.

We want to note that the optimal threshold for each localization method may not be exactly 0.5, and it varies for different models and images. To eliminate the influence of the threshold, we further compared several examples with the predicted masks of these models without binarizing the map. Figure 5 shows the results on AutoSplice forged images with two compression versions and different manipulation regions. We observed the influence of even mild compression on the localization performance when comparing the results in the odd rows on JPEG-100 compressed images and even rows on JPEG-90 images. Moreover, the size of the manipulation region appeared to be another crucial factor affecting the accuracy of localization. The majority of models struggled to detect forgeries containing large tampered regions in the AutoSplice dataset.

4.4.2 Fine-tuned Models

We fine-tuned two localization methods, CAT-Net [38, 39] and PSCC-Net [44], on the AutoSplice training set using JPEG-75 compressed images (as previously described in Section 4.3.2) to evaluate their performance in localizing pixel-level forgery. As expected, both models outperformed pre-trained models on the JPEG-100 and JPEG-90 testing sets, with the PSCC-Net model demonstrating significant improvement. However, the performance on the JPEG-90 set decreases obviously in comparison to the results on the JPEG-100 set, which aligns with the findings from Table 5.

5. Conclusions

This paper investigates the challenge posed by language-image generation models to media forensics and proposes a new approach that utilizes the DALL-E2 language-image model to splice masked regions guided by a text prompt. To ensure the creation of realistic manipulations, we have developed an annotation platform with human verification to validate reasonable text prompts. The approach has resulted in the creation of a new image dataset called *AutoSplice*, containing 5,894 manipulated and authentic images, including $3,621$ images generated by locally or globally manipulating real-world image-caption pairs, which we believe will be a valuable resource for future research. We have evaluated the effectiveness of several state-of-the-art forgery detectors in various testing scenarios. However,

our experiments with pre-trained models revealed unsatisfactory generalization performance in forgery detection and localization. Including our dataset in training could enhance the performance of existing models during in-domain testing. This finding emphasizes that fine-tuning on datasets with homogeneous characteristics results in significant performance improvements in media forensics. Nevertheless, achieving balanced performance across different JPEG compression quality factors and tampered region sizes remains a challenging task for forgery localization.

For future works, we will consider: first, exploring more advanced models to generate more realistic manipulated images to further challenge media forensics. Secondly, investigating approaches to improve the generalization performance of forgery detection and localization models to handle various types of image manipulations. Thirdly, conducting experiments to evaluate the performance of existing forgery detection and localization models on the proposed dataset under various testing scenarios and compare them with state-of-the-art approaches. Last but not least, exploring the potential of transfer learning approaches to enhance the performance of existing models on new datasets with limited training samples.

6. Impact Statement

The recent advancements in language-image models have led to highly realistic image generation from textual descriptions, which can pose a potential threat to media forensics. This paper provides a new image dataset called AutoSplice, created using the DALL-E2 language-image model to splice masked regions guided by a text prompt. The unsatisfactory generalization performance of existing forgery detection and localization models on the proposed dataset highlights the need for further investigation and improvement in this area. Future works proposed in this paper, such as exploring more advanced models and transfer learning approaches, aim to address these challenges and contribute to the advancement of media forensics research. Ultimately, this work will help detect image manipulations in various applications, including social media, journalism, and law enforcement, and contribute to ensuring the authenticity and reliability of digital media content.

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