A New Forgery Image Dataset and its Subjective Evaluation

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***Abstract*—The aim of this research paper is to present a new forgery image dataset with a thorough subjective evaluation in detecting manipulated images, considering various parameters. The original images were obtained from public sources, and meaningful forgeries were produced using an image editing platform with three techniques: cut-paste, copy-move, and erase-fill. Both pre-processing and post-processing methods were used to generate fake images. The subjective evaluation revealed that the accuracy of manipulated image detection was affected by various factors, such as user type, image quantity, tampering method, and image resolution, which were analyzed using quantitative data.**

***Index Terms*—Forgery Image Dataset, Image Manipulation, Subjective Assessment, Tampering Detection**

I. Introduction

The distinction between real and manipulated images is beginning to be significant as a result of the rapid advancement of the digital image environment. Since it becomes simpler for anybody to create fake images, digital image forensics has drawn a great deal of attention. Businesses, co-creation projects, studies, active learning, etc. all are beneficial areas of image manipulation [1]. As a result, benchmarking and developing digital forgery analysis have emerged as immediate concerns. Existing forgery image datasets, however, either contain a restricted range of forgery types or a limited range of standard quality evaluation. There have been many image manipulation techniques(cut-paste, copy-move, saturation, image morphing, erase-filling) reported in the bibliography that are using different transformations and alterations to achieve the desired goal [2].

Image forgery has received the attention of JPEG with Fake media WG[18] working on different use cases: fake news (e.g. social media manipulation), forgery media (e.g. document forgery and company/enterprise KYC (Know Your Customer) forgery data, media creation (media tracing/user-generated content/media processing). To tackle this new issue, we developed the LSBU Forgery dataset, a large collection of forgery images with three tasks for standard quality evaluation at the image level: 1) a forgery image dataset has been generated from publicly available original photos. Such a dataset is of general context, taking into account JPEG work, 2) Forgery images have been produced utilizing three-way techniques (cut-paste, copy-move, and erase-fill), as well as two-way techniques (pre-processing and post-processing). 3) Image quality, tampering technique, and picture resolution have all been used to illustrate the standard subjective evaluation. LSBU Forgery Image is the publicly accessible forgery data collection (1000 real images), manipulations (1000 images with three distinct ways), and forgery image post-processing (2000 images with four classification labels: resizing, rotation, sampling, and sharpening). We thoroughly benchmark and analyse an existing LSBU forgery image dataset and derive several insightful observations. As the authors of [3] noted, having publicly accessible datasets is beneficial to the researcher community since it may serve as a foundation for comparing research outcomes; hence, we chose to publicly share the LSBU forgery image dataset at The subjective study site for the same dataset will be available at: https://deepimageevaluation.com/. To the best of our knowledge, this is the first dataset that includes many subjective ratings of these three tampered models.

Section II presents the related work with image editing tools and the existing image forgery dataset with their characteristics and limitations. Section III presents the LSBU image forgery dataset, its characteristics, and forgery image techniques used. Section IV gives the subjective evaluation that has been used, and Section V presents the conclusion.

II. RELATED WORK

A. Image editing platform

There exist many tools that can be used for image editing, such as Adobe Photoshop (best for overall editing) [4], Corel PaintShop Pro (best for beginners) [5], Skylum Luminar (best for photographers) [6], Adobe Lightroom (best for online editing) [7], and Skylum Aurora HDR (best for HDR editing) [8]. Nowadays, many people do photo editing for several purposes; this turns into a crime when these images become forgeries. In many use contexts, image modifications are considered to be a critical component in gaining the trust of consumers. Different organizations have already helped to establish techniques that recognize and annotate updated media assets as they are shared [9]. On the other hand, changing the content of real-world photos without leaving apparent traces is easier, and it aids in the delivery of false information. DeepFaceLab [10] has been the most popular tool for delivering deep fake faces on the market. It is an open-source deep fake system that lets users swap faces in photos and on video. Using visual effects and visualization approaches, DeepFakes [11] demonstrates how people's reputations can be tarnished by substituting their faces with those of others. FaceApp [12] allows users to utilize Artificial Intelligence to modify their images. There are several ways to change the uploaded photo, such as using an editor to add an impression, make-up, smile, hair colors, haircuts, glasses, age, or beard. Reface [13] is one of the world's most well-known deep fake programs. It uses face-swapping AI to impose its face on images, memes, and GIFs. Deepfakes Web [14] is a web service that allows anyone to produce deep fake films and share them on the Internet. Deep learning is used to absorb the varied intricacies of face data. Apart from these, well-known platforms for deep-faking images and videos include Wombo [15], Deepfake Studio [16], and MyHeritage [17].

B. Exisitng forgery image dataset

The Columbia Dataset [21] was the first of several publicly accessible datasets for studying image manipulation. It was created in 2004 when the Columbia picture splicing detection validation dataset was made public. This is the first publicly accessible dataset for studying image manipulation.The cut-paste tampering method was the focus of the two Columbia datasets. CASIA's team established a web portal in 2009 in response to the increased need for larger assessment datasets and more realistic altered photos. The CASIA 1.0 collection contains a total of 1721 photos; 800 are authentic and 921 have been tampered [22] and CASIA 2.0 includes 7491 original and 5123 forgery images. The forgery images have been post-processed.

Datasets MICC-F220 and MICC-F2000 have been developed by the MICC team to support their investigation of copy-move detection [23]. The dataset includes 110 manipulated and 110 legitimate images. Amerini et al. [24] released the MICC-F600 in 2013 as an addition to their original study. It contains 440 original images and 160 tampered images. For the 160 tampered images, ground truth masks are provided.

In 2012, the Image Manipulation Dataset (IMD) [25] has been designed to evaluate copy-move tampering. ”Snippet” is an essential region manually selected in this dataset. Both the original images and fragments are mixed in various ways to generate manipulated images.

Snippet alterations and post-processing methods on forgery detection systems have been studied in the CoMoFoD compact picture dataset [26].

In Coverage Dataset [27], all the tampered images were included in this dataset as copy-move forgery images with a ground truth mask. It has a particular interest in photos of ”similar but genuine objects” (SGO) [27]. Due to the SGO, it is more difficult for algorithms to make a distinction between copy-move and authentic images.

This is the only dataset that includes three tampering approaches. The Wild Web dataset [27] targets filling up space in manipulating image assessment. There are no genuine images in the dataset because all of the images were retrieved from the web and social media channels.

C. State-of-the-art in subjective assessment of forgery images or related topics

The subjective assessment of forgery images is an important field of research in digital forensics. It involves the evaluation of the authenticity of an image, i.e., whether it has been tampered with or not, based on human perception. Over the years, various methods have been proposed to perform a subjective assessment of forgery images. In this section, we will discuss the state-of-the-art in this area.

One of the most widely used methods for the subjective assessment of forgery images is the ”Double Stimulus Continuous Quality Evaluation” (DSCEQ) method. This method involves presenting a pair of images, one original and the other manipulated, to human subjects and asking them to rate the degree of similarity between the two images. The ratings are then used to evaluate the authenticity of the manipulated image. The DSCEQ method has been used in several studies and is effective in detecting various types of image manipulations, such as compression, filtering, and resampling [28].

Another method that has gained popularity in recent years is the ”Visual Question Answering” (VQA) method. This method involves presenting a series of questions about an image to human subjects and asking them to answer based on their perception. The questions are designed to probe different aspects of the image, such as its content, context, and quality. The VQA method is effective in detecting image manipulations such as object removal, object insertion, and image synthesis [29].

In addition to these methods, several other approaches have been proposed for the subjective assessment of forgery images, including the ”Comparative Image Analysis” (CIA) method, the ”Perceptual Image Quality Assessment” (PIQA) method and the ”Visual Perception-based Image Authentication” (VPIA) method. These methods differ in their approach, but they all rely on human perception to evaluate the authenticity of an image [30]. Overall, the state-of-the-art in subjective assessment of forgery images is constantly evolving, with new methods and techniques being proposed and tested. The methods discussed in this section are just a few examples of the many approaches that have been proposed, and there is still much research to be done to improve the accuracy and reliability of these methods. Nevertheless, subjective assessment of forgery images remains an important area of research in digital forensics, and it is likely to continue to grow in importance as image manipulation techniques become more sophisticated. The features of the dataset are contrasted with those of other manipulated datasets in Table I(from the existing paper).The LSBU forgery dataset is a brand-new dataset that we suggested intended for the research and instruction of image modification detection methods. We attempted to develop a standard number of semantically significant forgeries for each category, which we fully discuss in the next section.

III. LSBU Forgery Image Dataset

LSBU dataset considers both high and low resolutions and it is availabe in IEEE dataport [31]. The forgery images have

Dataset	Year	Authentic	Manipulated	Forgery model	Image dimensions	Image format	Post-processing	Color
Columbia gray	2004	933	180	Cut-paste	128×128	BMP	No	No
Columbia color	2006	912	183	Cut-paste	757×568 , 1152×768	TIFF	Yes	Yes
CASIA v1.0	2009	7491	800	Cut-paste	384×256	JPEG	No	Yes
CASIA v2.0	2009	5123	921	Cut-paste, Copy Move	240×160, 900×600	TIFF JPEG	Yes	Yes
MICC-F220	2011	110	110	Copy-move	722×480, 800×600	JPEG	No	Yes
MICC-F2000	2011	1300	700	Copy-move	2048×1536	JPEG	No	Yes
IMD	2012	48	48	Copy-move	3000×2300	JPEG PNG	Not Needed	Yes
MICC-F600	2013	440	160	Copy-move	800×533, 3888×2592	JPEG, PNG	Yes	Yes
CoMoFoD	2013	5200	5200	Copy-move	512×512	JPEG PNG	Yes	Yes
Wild Web	2015	0	10646	Cut-paste, Copy Move, Erase-fill	Multiple dimensions	Multiple formats	Yes	Yes
COVERAGE	2016	100	1000	Copy-move	Multiple dimensions	TIFF	No	Yes
LSBU	2022	1000	3000	Cut-paste, Copy Move, Erase-fill	Multiple dimensions	JPEG, TIFF ,BMP	Yes	Yes

TABLE I
FORGERY IMAGE DATASET COMPARISON

been created using three different methods: cut-paste, erase-filling, and copy-move. To create the fake images, both pre-processing, and post-processing are utilized. This includes sharpening, enhancing color and size, blurring, and adjusting exposure. Resizing, rotation, sampling, and sharpening are all included in the next generation of fake photos.

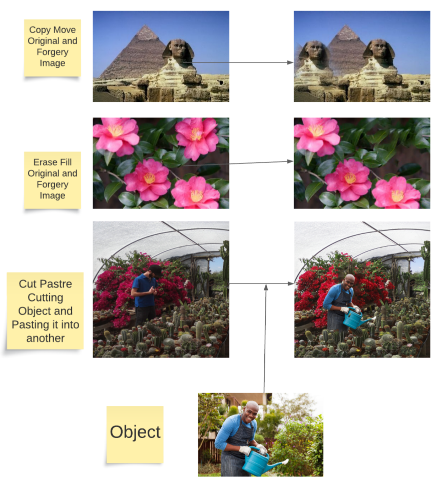

Fig. 1. A view of forgery techniques results with an example image.

A. Copy-move model

Copy-move forgery is a common type of image tampering where a region of an image is copied and pasted to a different location within the same picture to conceal certain aspects of the original image. It involves selecting an object from a source image and moving it to a similar region in the same image, with post-processing applied to produce the final forgery image. This approach is widely used in creating tampering datasets for forgeries due to its ease of implementation and minimal post-processing requirements. The copy-move forgery approach is prevalent and compromises the integrity of the original image, making it a popular choice for those who seek to manipulate images for deceptive purposes.

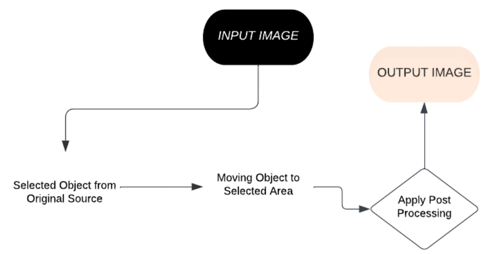

Fig. 2. Copy Move Model.

B. Cut-Paste Model

The cut-paste tampering model is a method of image manipulation where multiple images are merged by replacing a manipulated region with a component from a different reference image. This approach requires extensive post-processing such as edge blurring, color enhancement, sharpness, and smoothing methods. It is less popular among researchers because of the time and effort required to execute, but it is an effective method for creating tampered images that are less detectable than those created using the copy-move approach. This tampering model involves selecting a region from an original image, removing it, and pasting a corresponding region from another image into the original image. While less visible than copy-move region duplication, cut-paste tampering can still be detected using advanced image forensics techniques.

C. Erase-Fill Model

The erase-fill technique is a method of image inpainting used to remove unwanted components from an image and fill the remaining gaps with patterns from the surrounding area. Its primary goal is to restore damaged or missing portions of an image. The working strategy of the erase-fill tampering model involves removing selected objects from sources and applying various post-processing approaches before publishing forgery images to make them difficult to detect by human eyes. The post-processing approaches used for this model's forgery images include saturation, color adjustment, and sharpness techniques. Overall, the erase-fill technique is useful for restoring and manipulating images, respectively, but their high

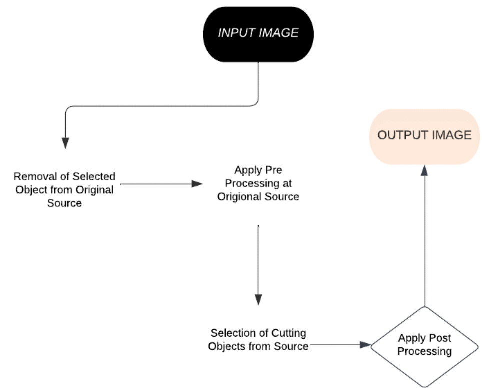

Fig. 3. Cut Paste Model.

post-processing requirements make them less commonly used compared to other tampering models.

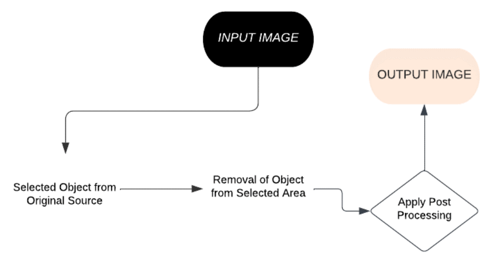

Fig. 4. Erase Fill Model.

D. Other Forgery Models

Forgery images are constructed with three tampered models that are available with both image resolutions. After that, four significant post-processing approaches were applied to newly constructed forgery images to contribute. "Resize," "Rotation," "Sampling," and "Sharpen" are the postprocessing options. In resize, all images are converted to one fixed dimension (640×480). Rotation is available both clockwise and anti-clockwise with a random selection of 15–90 degrees (15°, 30°, 45°, 60°, 75°, and 90°). High and low-resolution tampered images are available in 24-bit and 32-bit at their sources. So, sampling post-processing is applied to both image quality and fixed values (like 24-bit to 8-bit 1 and 32-bit to 8-bit) [32]. A carefully selected radius is taken into account for sharpening methods.

IV. LSBU Forgery Image Dataset: Subjective Evaluation

For the subjective evaluation of the LSBU Forgery image dataset, a website has been developed with all the original and forgery images (a total of 3000 images). For every participant, different images have been randomly selected.

A. Human observer dataset assessment

Humans' ability to identify forgery images has been evaluated by conducting a study with 200 subjects, including both experts and novices. A website has been used for this experiment (https://deepimageevaluation.com/)

- The front page presents all the details about this assessment process.
- A separate page is used so that the subjects are trained with different forgery samples. The image evaluation button is connected to a login form where every participant enters his/her anonymized data before starting the evaluation.
- The user is entered on the main page where he/she must complete 10 queries (every query presented a single image with one specific question and answer range).
- Users from three European academic institutions have participated as volunteers. Every user evaluates 10 different images.
- Each image is evaluated by the users with a relevant confidence range from 0 to 1(if the image is genuine, then the user should select 0 and if the image is a forgery, then the user should select 1 and if the image has some partial changes, then the user can select a value in the range of 0.1- 0.9).
- Users' responses are saved in the backend system along with the corresponding image numbers.

B. The influence factor in the evaluation

Our main goal is to evaluate the ability of users to detect forgery and original images. Several types of factors have been considered in this assessment and all factors' accuracy was measured using a basic percentage calculation process.

1) User Type: The study evaluated image editing proficiency in two groups of participants: experts and novices.

- Experts have been defined as individuals with knowledge and experience in image editing, particularly those with a computer science background. On the other hand, novices were individuals who are new to the field or lacked experience. The evaluation involved 76 experts and 124 novice subjects, respectively.
- The results of the study have been significant differences in performance based on user type. The accuracy rate for novice users was 36.40%, while for expert users, it was 43.20%.

2) Image quality: Image forgery approaches are significantly affected by image resolution. In this study, the dataset consisted of 2000 images, with an equal number of low and high-quality images.

- Due to the random selection process of subjective evaluation, only 1094 low-resolution images and 906 high-resolution images were utilized in the overall assessment.
- In Image quality accuracy percentage,36.65% low-resolution, and 43.60% high-resolution images were perfectly detected by participants.

The assessment accuracy has varied depending on the image resolution, with high-definition accuracy being higher than standard-definition accuracy. Standard-definition forgery images are easier to match neighboring pixel values, edge smoothing, sharpness, or other types of processing than high-definition forgery images. This finding highlights the importance of considering image resolution in image forgery detection and prevention.

3) Forgery type accuracy: One objective of this assessment is to evaluate the accuracy of different models in creating fake images that resemble the original ones.

- Out of the 2000 images used in the assessment, 1000 are forgeries, with 246 images from cut-paste models, 436 images from erase-fill models, and 242 images from copy-move models.
- Depending on the forgery type, 27.2% cut-paste, 46.6% erase-fill, and 26.2% copy-move forgery images have been identified correctly by the user.

The findings of this assessment highlight the importance of considering forgery techniques and image quality when evaluating the accuracy of image detection models. The lower accuracy of cut-paste forgery detection suggests that this technique is more challenging to create and, therefore, more difficult to detect. However, the higher accuracy of erase-fill forgery detection indicates that these techniques are easier to see and may be more common in practice. Further research can build on these findings to develop more effective strategies for detecting different types of image forgery.

V. LSBU Forgery Image Dataset: Quantitative Analysis

A. Scatter plot of percentage of correct and incorrect choices for each participant vs. their age

The scatter plot shows a graphical representation of correct and incorrect answers to a question, with the added dimension of age as a predictor of accuracy. The x-axis represents age, while the y-axis represents the number of correct answers. Each data point in the plot represents a response to the question, with the coordinates of the point corresponding to the participant's age and the number of correct answers. The story shows that regardless of age, most participants mispredicted the response. However, there appears to be a higher concentration of accurate predictions among participants in their 20s and 30s. This suggests that age may play a role in predicting accuracy, but other factors are also likely necessary. Overall, this scatter plot provides a proper visual representation of the relationship between age and accuracy in predicting the answer to the question.

B. Correct vs. Incorrect choices Density Estimation plot

Fig. 5 plot shows a graphical representation of the distribution of correct and incorrect predictions made by users on a set of images. The x-axis represents the index of the image, while the y-axis represents the density of correct or inaccurate projections. The plot shows that the density of correct predictions initially increases until the 0.025 indexes and then decreases. In contrast, the density of incorrect predictions initially decreases until the 0.025 indexes and then increases. Both curves eventually reach zero, with the correct angle ending at the 95th index and the wrong curve ending at the 100th index. This suggests that users are more accurate in their predictions at the beginning of the dataset, with accuracy decreasing over time.

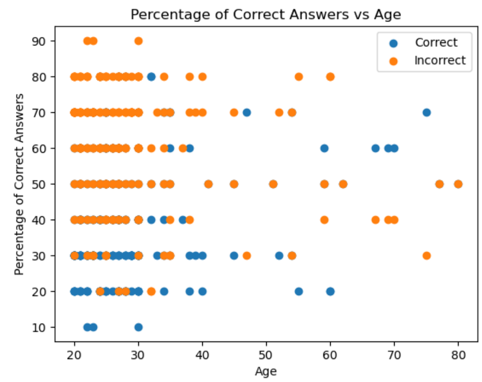

Fig. 5. Correct vs. Incorrect vs. Participant age

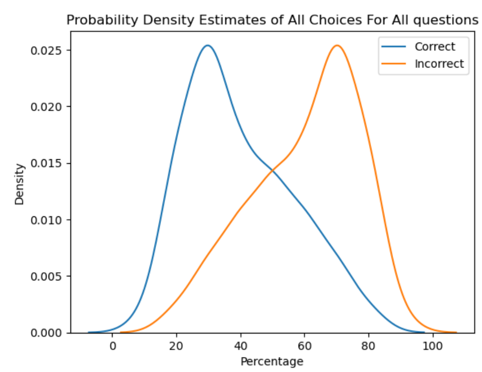

Fig. 6. Probability Density Estimation Plot

C. Overall Accuracy

The overall subjective accuracy achieved was approximately 39.7%. This accuracy has been measured by user feedback. Accuracy measurement with a forgery detection model is essential for every forgery image dataset for creating benchmark standards, and this personal investigation will greatly influence forgery image dataset acceptability.

The dataset subjective evaluation's overall accuracy rate has shown that the manipulation techniques are highly effective, and users can accurately distinguish between authentic and manipulated images. This underscores the unique nature of the three manipulation techniques utilized in the study. Despite the low accuracy rate, the dataset provides a valuable resource for researchers working in forensic media. It can serve as a benchmark for evaluating the performance of forgery detection algorithms. Overall, this study highlights the challenges of detecting image manipulation and underscores the importance of developing effective detection techniques to combat the proliferation of manipulated images in modern media. Improved forgery detection and prevention techniques can help ensure the integrity of digital images and videos, which has significant implications for various industries, including journalism, forensics, and entertainment.

VI. Conclusion

In summary, while some forgery image datasets are currently available, only a limited number contain manipulated images with diverse contexts and accompanying subjective analysis. This paper presents a generic forgery image dataset that includes a comprehensive subjective study and data analysis. Our dataset, available online at the IEEE DataPort [31], has been designed and assessed with a proper structure. Our analysis shows that it can be a benchmark for manipulated images in forensic media. The generation of manipulated datasets has become an area of interest for researchers, and our dataset, along with its accompanying subjective study results, can significantly aid in the evaluation of forgery detection algorithms. The forgery images are generated using three tampering models, and our subjective evaluation shows less than 40% overall accuracy for all models. Overall, our contribution provides a valuable resource for future research in the area of forgery image detection and analysis.

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