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Detection of Copy-Move Forgery in Digital Images Using Singular Value Decomposition

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Abstract: This paper presents an improved approach for detecting copy-move forgery based on singular value decomposition (SVD). It is a block-based method where the image is scanned from left to right and top to down by a sliding window with a determined size. At each step, the SVD is determined. First, the diagonal matrix's maximum value (norm) is selected (representing the scaling factor for SVD and a fixed value for each set of matrix elements even when rotating the matrix or scaled). Then, the similar norms are grouped, and each leading group is separated into many subgroups (elements of each subgroup are neighbors) according to 8-adjacency (the subgroups for each leading group must be far from others by a specific distance). After that, a weight is assigned for each subgroup to classify the image as forgery or not. Finally, the F1 score of the proposed system is measured, reaching 99.1%. This approach is robust against rotation, scaling, noisy images, and illumination variation. It is compared with other similar methods and presents very promised results.

Keywords: Forgery image; forensic; image processing; region duplication; SVD transformation; technological development

1 Introduction

Nowadays, digital images have become part of daily life due to the high growth of technology and the development of the internet. This led to easy access to images and multimedia, processing them, transferring and quickly altering image details, and developing tampered images [1]. Digital images are almost used in every branch of our life and scientific fields. It is used in authentication, court, law, medical, industry, Remote sensing, forensics, machine vision, etc.

Editing and changing digital images become easier for anyone with the advancement of various low-cost hardware and software tools such as Adobe Photoshop, Corel draw, etc. As shown in Fig. 1 [2], many changes can be made to images.

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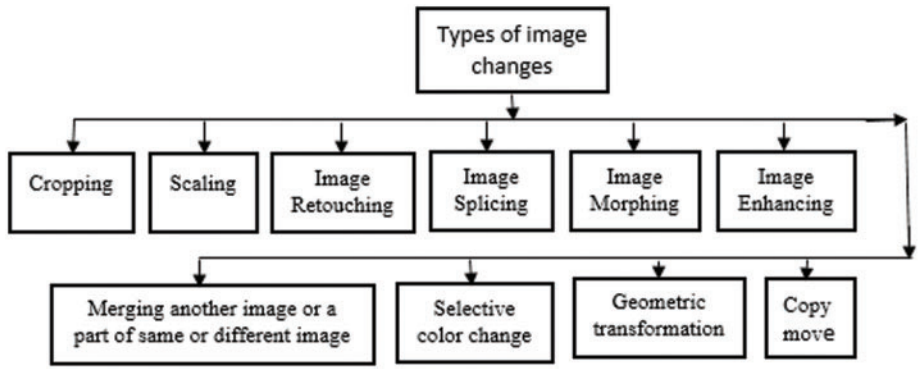

Figure 1: The possible changes that can be made to images

With the extensive use and transmission of digital images, authentication becomes very important to increase the trust in the images [3]. Image forensics is an alternative method of authenticating. One of these methods is forgery detection. Digital Image forgery can be generally classified into two main types, active and passive, as shown in Fig. 2 [4,5].

Three types of passive image forgery can be made for digital images.

1.1 Image retouching focuses on reducing or enhancing some of the digital image features that make it a less harmful type of image forgery.

1.2 Splicing is implemented by combining two or more images, which hides some critical information from the original image [6].

1.3 Copy-move forgery (CMF) is the most popular type. It includes copying part of the image and then pasting this part into another region of the image. Of course, image editing can be made along with this operation, such as scaling, rotation, adding noise, etc. Unfortunately, it is not easy to detect this type of image forgery. In general, passive forgery detection can be categorized into block-based and keypoint-based methods [3]. Usually, the keypoint approach is based on one or more feature extraction techniques, such as Scale-Invariant Feature Transform (SIFT), Speeded Up Robust Features, or others [5,7,8].

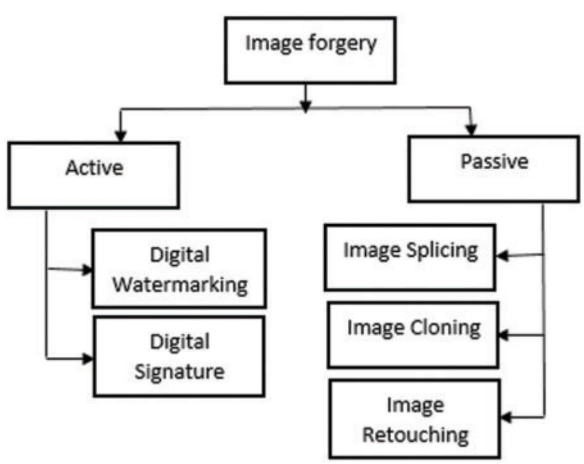

Figure 2: Types of image forgery

In this paper, we look to suggest a robust algorithm to detect copy-move forgery (also known as region duplication attack). Fig. 3 shows an example of this type of attack.

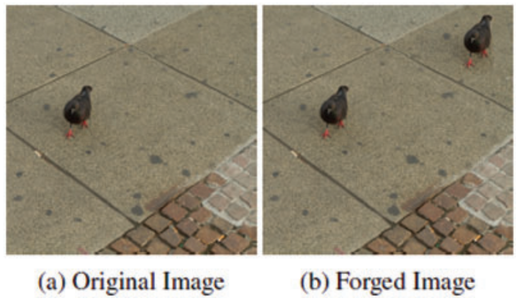

Figure 3: Effect of copy move forgery

The primary approach to detecting the same regions is block-based [9,10], which means they look for block pixels similar to the other block(s) in an image, where a gap is separate between them. Such methods help detect copy-move forgery, which occurs when an image region is replicated without being altered. However, approaches that entail region changes such as scaling, rotation, and image lighting variation are not as efficient for region duplication.

We will use a CASIA [11] and CoMoFoD dataset [12] that includes a set of color forgery images in the currently proposed method.

The rest of the paper is organized as follows: Section two presents the related works, while Section three focuses on the definition of singular value decomposition. In Section four, the proposed method methodology will be introduced. Then Section five specified results and discussion. Finally, the conclusion will be summarized in Section six.

2 Related Works

(Amerini et al., 2013) suggested a method for the detection of image forgery based on SIFT. Features extracted from images of the dataset MICC-F220 and MICC-F2000. This method deal with the rotation and scaling of the forged object. The False Positive Rate (FPR) and True Positive Rate (TPR) achieved are 8% and 100%, respectively [11].

(Uliyan et al., 2016) introduced a forgery detection method based on combined features of Hessian points and a centrosymmetric local binary pattern (CSLBP). The advantage of this method is invariant to scale, translation, and illumination, but on the other side, it is not invariant when the image is degraded by blur. The false-positive and true-positive rates are 8% and 92%, respectively [12].

(Alkawaz et al., 2018) proposed image forgery detection approach based on discrete cosine transform (DCT). This method works with gray images. The input image is divided into several overlapping blocks. For each block, the 2D DCT coefficient is determined. A feature vector is generated using zig-zag scanning in every block and sorted by lexicographic. Finally, the Euclidean distance is used to locate duplicate blocks [13].

(Huang et al., 2019) suggested a method to detect copy-move forgery based on superpixel segmentation and Helmert transformation. The first step of this method used the SIFT algorithm to extract the key points and their descriptors. Matching pairs is achieved by determining the similarity of key points based on the descriptor. These pairs are grouped based on the spatial distance by Helmert transformation to get coarse forgery regions. The isolated area will be removed. The advantage of this method is the robustness for rotation, scaling, and compression. The best recall and precision were 80% and 82%, respectively [14].

(Ali et al., 2022) Proposed a system based on deep learning to detect forgery images in the context of double image compression. Training the proposed model based on the difference between the original and recompressed images. The performance of this model was 92.23% as a validation accuracy [15].

3 Singular Value Decomposition (SVD)

In linear algebra, SVD is a critical topic by many famous mathematicians, which is a factoring of a true matrix and is utilized to elicit geometric and algebraic features of the image. SVD is a stable transformation for scaling and rotation invariance, it is a vigorous and trustworthy orthogonal matrix decomposition method, so it has become popular in many practical applications in signal and image processing and statistics [16]. A unique feature of SVD is its application on real (m, n) matrix, as Eq. (1). For any given matrix A∈Rm × n, there exists a decomposition

$$A = USV^T \tag{1}$$

such that

- U is an $m \times n$ matrix with orthonormal columns.
- S is an $n \times n$ diagonal matrix with nonnegative entries.
- V^T is an $n \times n$ orthonormal matrix.

We can visualize this decomposition in Fig. 4.

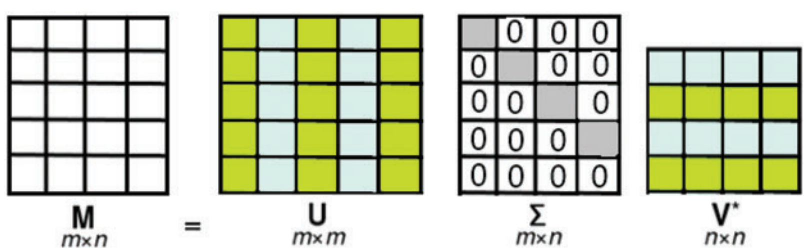

Figure 4: Decompose a matrix using SVD

4 Proposed Scheme

This proposal suggested a robust algorithm for detecting copy-move forger images based on the SVD transformation. The primary step to solving the problem of detecting copy-move forger is listed in Algorithm 1.

Algorithm 1
Input: RGB image
Output: Decision (Forgery or Not-Forgery image)
Step 1: Preprocessing
Step 2: Scan the image from left to right and top to down by sliding a window with a specific size.

(Continued)

Algorithm 1 Continued

Step 3: At each location of step 2, find the norm value of the (S) matrix, which represents the diagonal matrix achieved from the SVD transformation.
Step 4: Create many groups of the norms according to the norm values.
Step 5: Further divide each group into subgroups based on the 8-adjacency.
Step 6: Assign weights for sub-groups of the same size (± 1 *pixel*) and there is a distance between them.
Step 7: Determine the sum of the weights and number of sub-group for each norm.
Step 8: Image classified into forgery if the number of the subgroup in such norm is more than seven, and selected weights are greater than fifteen or less than nine.

The input image for this system is a color image. First, preprocessing for the input image is implemented, which includes (converting the RGB image into a gray image, image denoising by using a deep neural network (CNN), and resizing the image (most of the images in the dataset have a size of 256×384, so every image with a size larger or less than this size will be normalized to (256×384)).

A sliding window with size 11×11 will be scanned on the entire image from left to right and top to bottom. At each step, the SVD transformation will be calculated. The result of the SVD process will be three matrices. We are concerned with the diagonal matrix. The largest value of the diagonal matrix at each step is selected, called (the norm value), and stored in a matrix (has norm values and locations of a norm).

After scanning the entire image, the norm vector will be sorted in ascending order. This vector is divided into many groups (each group has a similar norm value), and groups with less than four pixels will be ignored.

We try to find the connected norms for each group according to the 8-adjacency. This process divides the group into several sub-groups (there is no connection between each sub-group with other sub-groups of the same norm). Each subgroup with less than three norms will be ignored. A weight for a group will be created according to the sub-group size (weight increase by one for every two subgroups has the same size or different by one).

Finally, two arrays will be created. The first includes the norm value and the corresponding weights, while the second consists of the norm value with the corresponding number of subgroups (left in the group). The two arrays are sorted in ascending order according to the weight and number of the subgroup. We select the first (highest) six norms of the first array (weight array) and the first ten norms of the second array (subgroup array).

Image classified as a forgery image if achieved the following condition:

"If the subgroup number in the selected norm is more than seven, and selected weights are greater than fifteen or less than nine."

Else it is classified as a non-forgery image. Fig. 5 shows the block diagram of the suggested algorithm.

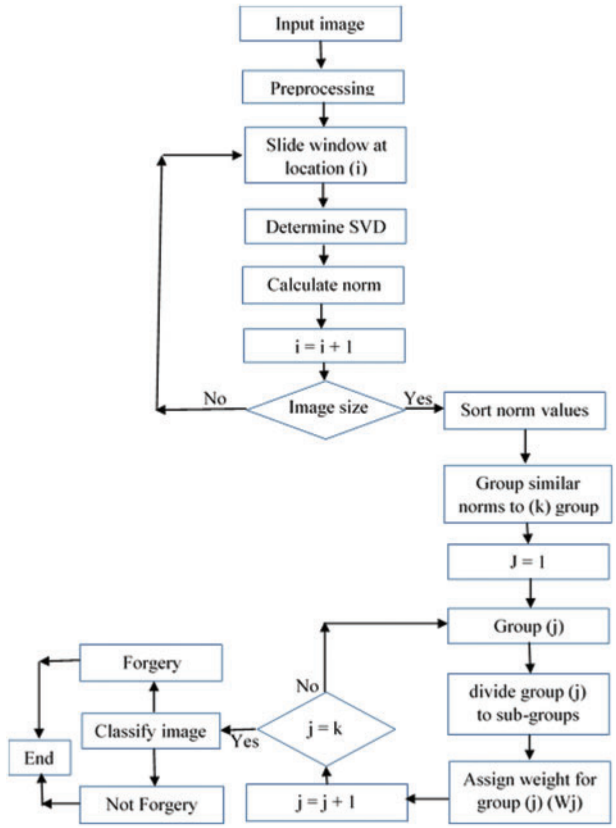

Figure 5: The block diagram for the suggested algorithm

5 Results and Discussion

Several tested experiments are conducted to assess the proposed schemes in this section. MATLAB 2018b is used to carry out the experiments. First, the approach was tested on 500 color stander images from the CASIA and CoMoFoD datasets. Animals, plants, structures, and some types of meals are among the original authentic images from two databases, Fig. 6 shows a sample of dataset images used in the current proposal. Second, Adobe Photoshop CS6 was used to create the altered images from the originals (scaling and rotation objects).

Precision as Eq. (2), recall as Eq. (3), and F1 score as Eq. (4) are used as performance assessments to measure the accuracy of the tampered images detection of the proposed algorithm [17,18].

$$\text{Precision} = \frac{T_P}{T_P + F_P} \tag{2}$$

$$\text{Recall} = \frac{T_P}{T_P + F_N} \tag{3}$$

$$\text{F1} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

where T_P is the true positive, F_P is a false positive, and F_N is a false negative.

Figure 6: Samples of the dataset's images used in the current proposal from CASIA and CoMoFoD datasets

The first test focuses on evaluating the performance of the suggested system when using different sliding window sizes. Forgery and non-forgery images are fed from the datasets into the system one by one, and the system's performance is assessed. The best performance is achieved when the block size of the sliding window equals 11 × 11, as shown in Table 1. This test is also regarded as a test for determining the best sliding window size that can be used in this proposal. The results are summarized in Fig. 7 in addition to Table 1.

Table 1: Evaluation of blocks size

Block size	Precision	Recall	F1
5 × 5	78.57	94.29	85.71
7 × 7	74.16	94.29	83.02
9 × 9	85.90	95.71	90.54
11 × 11	99.1	99.1	99.1
13 × 13	80.00	91.43	85.33
15 × 15	85.71	94.29	89.80
17 × 17	80.00	85.71	82.76

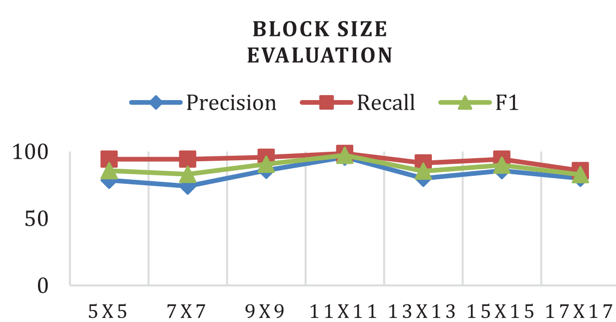

Figure 7: Block size evaluation of sliding window

The input image size has high effects on the performance of the proposed algorithm, so we test how the image size affects the results in the proposed algorithm and what is the best image size that can be used to get optimum accuracy. Fig. 8 shows the result of this test. We can conclude from this figure that the image size (256 × 384) is the best choice to get better accuracy.

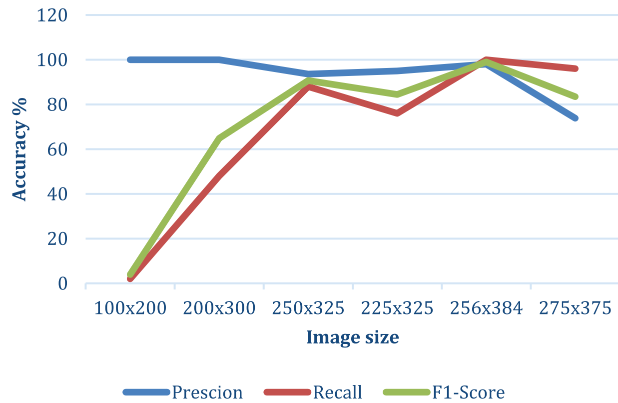

Figure 8: Effect of image size on accuracy

Also, the current proposal is tested when the duplicated object is rotated with different angles ranging from 20 degrees to 180 degrees. The testing results are tabulated in Table 2. As shown in Table 3, the suggested technique successfully detects all duplicated regions under rotation attacks from various angles. Fig. 9 shows a sample of rotated object images tested by the proposed scheme.

Table 2: Performance of the proposed method when the forged object rotates with different angles

Angle	Precision	Recall	F1 score
20	100	100	100
40	100	100	100
60	100	100	100
80	100	100	100
100	100	100	100
120	100	100	100
140	100	100	100
160	100	100	100
180	100	100	100

Table 3: Comparing many forgery detection techniques

References	Method	F1-score
Kafali et al. (2021) [19]	ResNet/VBI	51.6
Zhu et al. (2020) [20]	AR-Net/ASPP	45.52
Islam et al. (2020) [21]	GAN	96.48

(Continued)

Table 3: Continued

References	Method	F1-score
Zhong et al. (2019) [22]	Dense-InceptionNet	78.18
Ashraf et al. (2020) [23]	DWT	97.52
Ahmed et al. (2020) [24]	SVD/KS	95.9
Rathore et al. (2021) [25]	SVD/BWT	92.24
Cozzolino et al. (2014) [26]	DWT	94.7
Cozzolino et al. (2015) [27]	dense-field	94.26
Li et al. (2015) [28]	SIFT-RANSAC	94.98
Wang et al. (2018) [29]	Rg2NN	96.8
Wang et al. (2017) [30]	Rg2NN	96.1
Meena et al. (2020) [31]	FMT-SIFT	96.97
Singh et al. (2020) [32]	SVD/DCT	86.81
Proposed method	**SVD**	**99.1**

Note: Abbreviations: Volterra-Based Inception (VBI), Atrous Spatial Pyramid Pooling (ASPP), Generative Adversarial Network (GAN), Discrete Wavelet Transform (DWT), Kolmogorov Smirnov (KS), Biorthogonal Wavelet Transform (BWT), Fourier-Mellin Transform (FMT), Discrete Cosine Transform (DCT).

Figure 9: Sample of forgery images with rotating forged objects from CASIA and CoMoFoD datasets

The other performance testing of the proposed method is when the duplicated object is scaled. A sample of images when scaling forged objects is shown in Fig. 10. The proposed method successfully detected all the forgery and non-forgery images with scaled objects.

Figure 10: Sample of forgery images with a scaled object from CASIA and CoMoFoD datasets

For further analysis of the robustness of the proposed algorithm, we implemented various experiments on the forgery images where it is contaminated with noise. First, Gaussian noise is inserted in the tested images. Then, gaussian noises were added randomly, with zero mean and standard deviations of 0.2, 0.4, 0.6, and 0.8. In this test, 300 images were used. The F1-score accuracies are shown in Fig. 11. Although the proposed algorithm shows a robust behavior against the noise, the method performance did not affect when using noisy images.

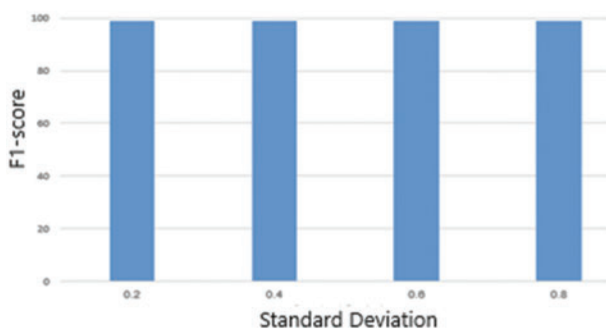

Figure 11: The F1-measure chart under attacks of additive white Gaussian noise

The result of detecting forgery images contaminated with noise is compared with other works, as shown in Fig. 12.

Also, the proposed method was tested with various image illumination, and we found that the F1-score for detecting forgery images was up to 99.1%. A sample of the image used in this test is shown in Fig. 13.

The elapsed time of the CPU for the detection of the forgery image was 18.5 s.

Finally, the suggested method results are compared with several similar methods, as illustrated in Table 3.

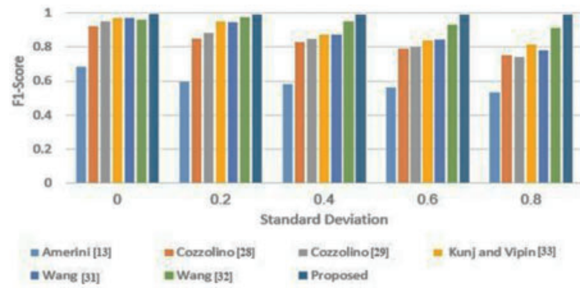

Figure 12: Comparing F1-score for different works under attacks of additive white Gaussian noise

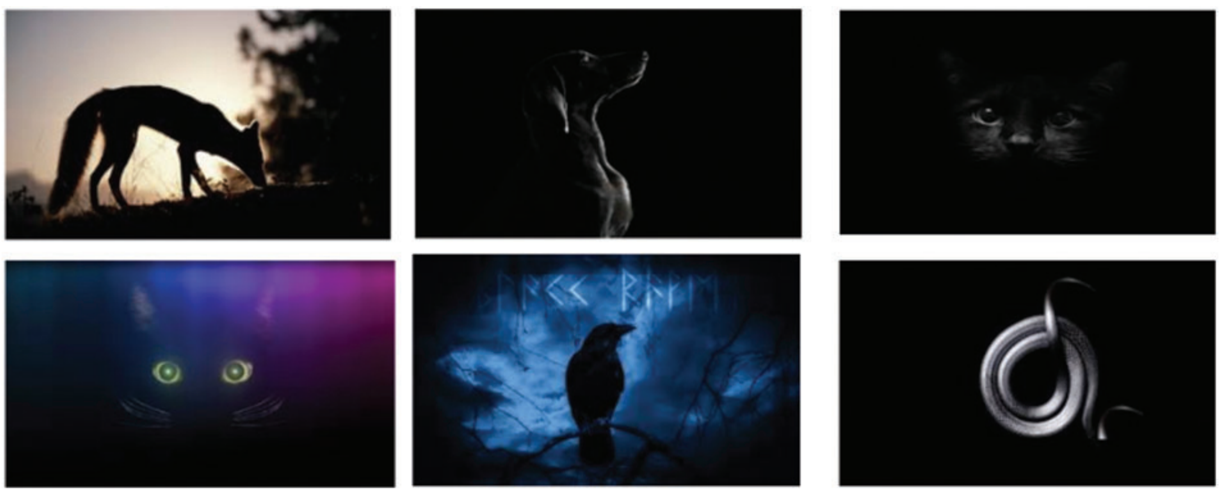

Figure 13: Sample of image with various illumination from CASIA and CoMoFoD datasets

6 Conclusions

This paper proposed a new enhancement of the SVD for digital image forgery detection. First, we used CASIA and CoMoFoD datasets to evaluate the proposed method. Then, a preprocessing technique was applied to convert the input images from RGB to grayscale, and the images were resized into 256×384. Next, the image was divided into 11×11 overlapped blocks. After that, we used the SVD (diagonal array) to extract features from each block.

The norm's value was also calculated for each block, finding similar norms. Finally, for each similar norms subgroups, the weight was calculated, and this led to deciding if the image was copy-move or not. The suggested method gives excellent results, and we proved it robust against rotation, scaling, noisy images, and illumination variation. Furthermore, when the introduced method is compared with other methods, it shows high performance, giving better results than most copy-move detection methods. For future work, we suggest using generalized singular value decomposition (GSVD) to detect the copy-move forgery, which has many features that need to be discovered.

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Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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