

Automatic multi-class classification of geographical indication-tagged tribal art using deep learning

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ABSTRACT

In the field of computer vision, deep learning has significantly improved automated image classification, yet the classification of Indian tribal artworks remains largely unexplored. These art forms exhibit substantial stylistic overlap, variations in color palettes, and complex hand-drawn patterns, making manual identification difficult and automated classification even more challenging. Existing methods for artwork recognition are limited by small datasets, domain-specific variations, and a lack of curated tribal art collections. This study addresses these gaps by developing a deep learning-based framework for the multi-class classification of three culturally significant Indian tribal arts: Manjusha, Gond, and Warli. A manually curated dataset of 900 images was augmented using geometric and color-based transformations to increase robustness. The model is built on the Inception-ResNet-V2 architecture using transfer learning. Experimental evaluation demonstrates high performance, achieving 98.21% testing accuracy and stable validation trends. The proposed approach provides a scalable baseline for tribal art classification, supporting digital heritage preservation and future development of retrieval or educational systems.

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1. INTRODUCTION

Governments worldwide are increasingly digitizing cultural heritage collections to improve accessibility and long-term preservation. Indian tribal art, a crucial component of this heritage, appears in paintings, textiles, crafts, and contemporary design. However, despite its cultural importance, automatically classifying tribal artwork remains a non-trivial task. Many tribal art forms share similar visual structures, recurring geometric motifs, and overlapping color schemes, making it difficult even for experts to distinguish them reliably.

Recent advances in deep learning have shown strong performance in image recognition tasks such as fine-art classification, cultural heritage analysis, and texture-based pattern recognition. Several studies have employed CNNs, hybrid models, or transfer learning to classify artworks or heritage imagery, achieving high accuracy under curated datasets. However, these approaches primarily focus on western art genres, Chinese brushstroke styles, or heritage monuments, leaving Indian tribal art largely unaddressed. Moreover, the absence of publicly available tribal art datasets further limits progress in this domain.

This study addresses these gaps by investigating deep learning techniques for the classification of three major Indian tribal art forms: Manjusha, Gond, and Warli. The objective is to design an effective and robust model capable of distinguishing these visually similar art styles, while establishing a baseline dataset

and methodology that can support future research. Using transfer learning with Inception-ResNet-V2 and extensive data augmentation, the proposed framework provides a scalable solution for tribal art classification and contributes to the digital preservation of indigenous cultural assets.

Figure 1 illustrates ten prominent Indian folk-art traditions. Figure 1(a) shows Warli art characterized by geometric stick figures, while Figure 1(b) presents Khovar art known for its mural-style motifs. Figure 1(c) depicts Tanjore/Thanjavur art with rich relief and gold foils. Figure 1(d) displays Kawad storytelling panels. Figure 1(e) shows Madhubani art with intricate mythological scenes. Figure 1(f) presents Pattachitra scroll paintings. Figure 1(g) features Saura art based on tribal rituals. Figure 1(h) shows Gond art, identifiable by line patterns and shading. Figure 1(i) presents Bhil art using dot patterns, and Figure 1(j) illustrates Manjusha art with its distinctive linear borders and symbolic colors.



Figure 1. Prominent Indian folk arts: (a) Warli, (b) Khovar, (c) Tanjore/Thanjavur, (d) Kawad, (e) Madhubani, (f) Pattachitra, (g) Saura, (h) Gond, (i) Bhil, and (j) Manjusha

Gond art [1] is a form of the Gond community of Madhya Pradesh is for preserving and communicating their culture. Originating from the state of Madhya Pradesh and nearby states, this art is carved on the mud walls. These paintings are rich in details, lines, colors, mystery, and humor. These paintings are also drawn on paper, canvas, and cloth. In these paintings, lines, dots, and dashes are important features. The powerful representation of natural elements with the recurrent presence of design is the sound feature of this art form. This painting is drawn during major festivals such as Holi, Diwali, and many others. These paintings are so good in quality that they can last for about 20 years even without any tampering.

Manjusha art [2] is the heritage of Anga Pradesh. According to Vedic historians, this art is the art of the indus-valley civilization. In which the story of 'Bihula Bishari' is depicted. It is the first folk traditional art in Asia. Which is a full story. This art originated in the state capital, Champa, which is currently located in Bhagalpur Bihar. Pink, yellow, and green colors are mainly used in painting. These colors have esoteric and symbolic meanings. The pink and yellow colors signify excitement and exuberance, while green is a symbol of gloom and growth. Borders in Manjusha art include designs of Belpatra, Lehariya, Triangle, Mokha, and a series of Snakes. The traditional artist of Manjusha painting, Chakravarti Devi used natural colors. But now posters, water, oil, and 'acrylic color' are being used.

Belonging to the state of Maharashtra, Warli tribal art [1] is famous for its elementary wall paintings. It is one of the finest examples of folk paintings. In this, basic geometrical shapes are used such as squares, circles, and triangles. These paintings are carved in white colour (bamboo is used as a brush) on a dark red coloured background. The painting portrays hunting, festivals, fishing, farming, dancing, and other scenes of daily life. The first column in Figure 2 contains Gond art images, Manjusha art samples are in the second column and the last column represents Warli art images.

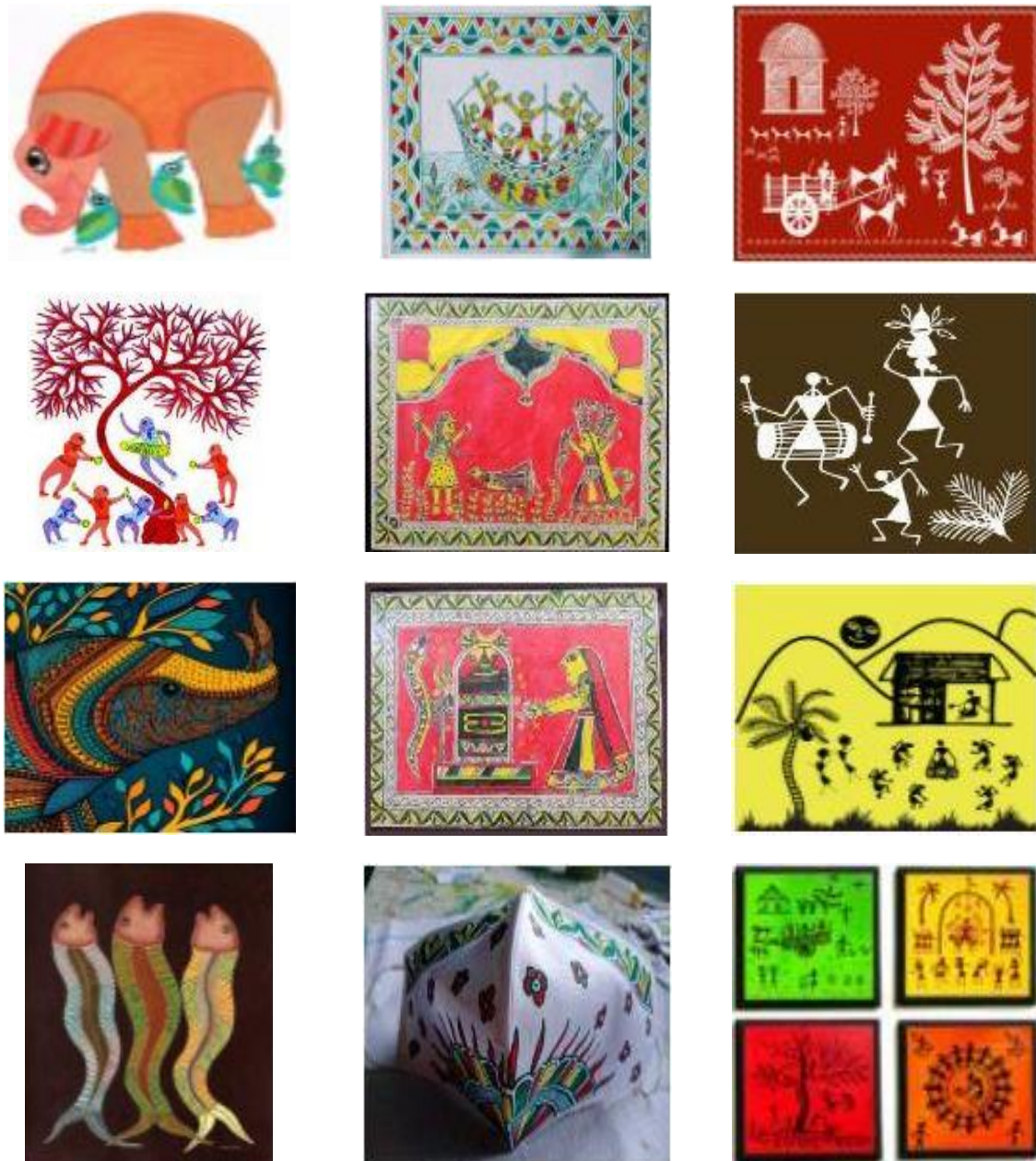


Figure 2. First column-gond art, second column-Manjusha, and third column-Warli art

2. LITERATURE SURVEY

Computational algorithms and deep learning models have been widely explored for the classification of artworks, where the task generally involves categorizing a painting by its genre, visual style, or creator. Early work in this domain achieved promising accuracy using deep networks for traditional Chinese painting (TCP) classification across six stylistic themes [3]. Other studies have introduced handcrafted features such as brushstroke patterns to distinguish Chinese from Western paintings, demonstrating that texture-level cues can significantly enhance binary classification [4]. Geometric motif analysis has also been applied to mosaic artworks, where CNNs successfully recognized shapes and patterns even under partial deformation [5]. Beyond these, sparse metric learning combined with hybrid SVM-ANN modeling has been used to classify paintings by artist, genre, and style, though performance remains moderate due to the high variability in fine-art datasets [6].

More recent works adopt deep learning pipelines that integrate both global and local image cues. Dual-path networks utilizing RGB and stroke information [7], and patch-based CNN architectures that feed into shallow neural networks [8], have shown effectiveness in addressing intra-style ambiguity. Large-scale

datasets such as WikiArt have enabled CNN-based genre recognition [9], and additional research has explored semantic and structural cues for ranking similarity or handling artist-level classification using Markov random fields and CNN hybrids [10], [11]. Transfer learning has also gained traction in heritage imaging, with models successfully classifying Indian cultural heritage sites using large image corpora [12], while other studies have used CNN variants to classify Madhubani art and related cultural motifs [13].

Parallel developments across domains such as face-mask detection [14], skin lesion analysis [15], digital art processing [16], music modeling [17], agriculture [18], medical imaging [19], marketing [20], and defense [21] reiterate the broad effectiveness of deep CNNs for complex visual recognition tasks. Works involving flower recognition using segmentation-assisted CNNs [22], DenseNet-MLP hybrids [23], and CNN-based logo recognition [24] further reinforce the versatility of deep learning architectures. Complementing these contributions, surveys on data augmentation highlight the critical need for synthetic sample generation, especially in scenarios involving small or imbalanced datasets-conditions frequently encountered in cultural and artistic image classification [25].

Table 1 summarizes the key datasets, classes, architectures, and reported performances from these studies. While the literature demonstrates that deep CNNs and transfer learning approaches can achieve strong results across various art and pattern domains, most rely on large, standardized datasets or visually distinct styles. In contrast, Indian tribal artworks such as Manjusha, Gond, and Warli share overlapping motifs, hand-drawn variations, and similar color palettes, making them harder to classify automatically. Moreover, no publicly available dataset exists for these art forms, and no prior work has attempted their multi-class classification. This gap highlights the need for a robust deep learning framework tailored to small, visually similar cultural art datasets-an objective addressed in the present study.

Table 1. Summarized details of the recent works

Work	Dataset	No. of classes	Architecture/ML algorithm	Performance
[1]	1170 TCP images	6	NASNetLarge + SVM	99.66 %
[2]	1083 Chinese ink paintings and 1766 Western paintings	2	SVM	89.04%
[3]	407 mosaic images	5	CNN	97.05%
[4]	81,499 images of fine-art paintings	Genre:9 Artist: 9 Style: 15	Hybrid Support Vector Machine-Artificial Neural Network	Genre:64.34% Artist: 68.45% Style: 49.78%
[5]	Gallerix dataset of 160,000 images	Genre: 8 Artist: 18 Style: 20	131-layer DPN	Genre:52.27% Artist: 34.4% Style: 63.69%
[6]	Dataset1: 30870 Dataset2: 85000 Dataset3: 19320	Dataset1: 6 Dataset2: 23 Dataset3: 19	CNN and shallow neural network	Dataset1: 67.16% Dataset2: 66.71% Dataset3: 77.53%
[6]	Dataset1: 30870 Dataset2: 85000 Dataset3: 19320	Dataset1: 6 Dataset2: 23 Dataset3: 19	CNN and shallow neural network	Dataset1: 67.16% Dataset2: 66.71% Dataset3: 77.53%
[7]	WikiArt	7	CNN	81.77%
[8]	Dunhuang mural dataset	2	ANN	98%
[9]	WikiArt: 20405 PaintingDb: 1300	WikiArt: 23 PaintingDb: 13	MRF-CNN	WikiArt: 72.89% PaintingDb: 76.92%
[10]	Indian Digital Heritage Space Monuments data: 108080	9	Transfer learning	98.75%
[11]	Own database of Madhubani art forms	5	Transfer learning	98.82%
[12]	Kaggle: 1376 images of width and height of 224×224	2	CNN: MobileNetV2	99.99%
[13]	ISIC-2018 dataset of skin lesion dermoscopic images of the lesion	7	CNN: DenseNet and Inception-v3	81%

3. PROPOSED APPROACH

Transfer learning is used to reduce the training time. We have used Inception ResNetV2, without the top layer, as a base model. Inception-ResNet-v2 [26] merges both the concepts of Inception-v3 and ResNet [27] architectures. Inception-ResNet-v2 has a stem as in Inception-v3 and Residual blocks as in the ResNet model. But, inside every residual block, filter concatenation is carried out and the filter sizes vary for these residual blocks.

In transfer learning, there are mainly two phases: Feature extraction from the input image and the second phase is fine-tuning of the base model. As the trained model, we can use the pre-trained weights based on the available datasets. In our model, we have chosen “imagenet” weights. The last layer of the base model includes the classification softmax layer. As we want to have other layers on top of it, we need to set `include_top = False` to remove the classification layer.

When the dataset is either not available at all or it is very less, data augmentation is essential to make the model robust, reliable, and accurate [28]. The proposed model is depicted in Figure 3. It is clear from the figure that all three sample images have a 'circle' as a prominent shape and they also have similarities in terms of colors used. It is the minute details in each that can separate one art form from the other.

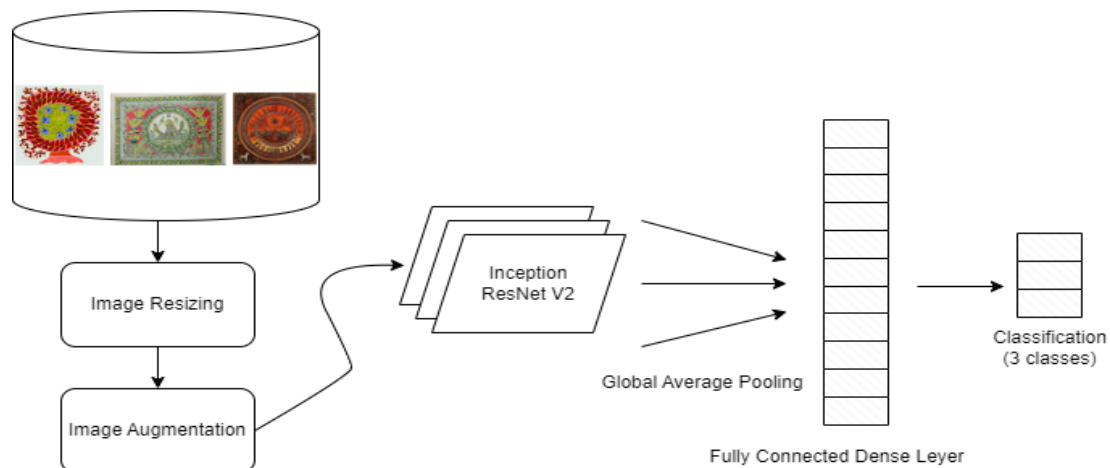


Figure 3. Proposed approach

4. DATASET

In this work, we have considered three different folk arts, namely Manjusha, Warli, and Gond. The art is popular on the cover page of diaries, on the pen stand, and in the wall clock background. Some of the sample images of pen stands are shown in Figure 4. Figure 4(a) is a Gond art pen stand, Figure 4(b) is Manjusha art pen stand, and Figure 4(c) is Warli art pen stand.



Figure 4. Pen stands with art work, (a) Gond art pen stand, (b) Manjusha art pen stand, and (c) Warli art pen stand

There is no readily available dataset, so we have manually created a dataset. The dataset consists of 300 images for each artwork and these images are downloaded from various websites. In total, there are 900 images. Deep CNNs need a large dataset which is not possible to create manually so we have used data augmentation techniques to increase the size of the dataset. Data augmentation makes the model more robust which can efficiently handle new images during the testing. We have applied rotation, flipping in x and y directions, zooming, shear transformation in x and y directions, and cropping algorithms for data augmentation. The data augmentation gives a reliable number of samples for each tribal art.

To use the base model, we have used `tf.keras.applications` which contain many successful models. The paper uses Inception-ResNet -v2 as a base model and applies a transfer learning approach with data augmentation techniques for classification.

The dataset is divided into training, validation, and testing. Out of 900 images, 180 images (20%) are used for validation. There is a separate dataset of 180 images (60 images for each class) for the testing of the model. The suggested CNN architecture is shown in Figure 5. In the pre-processing step, the whole dataset is resized to 331×331 to make it suitable for the input layer.

Layer (Type)	Output Shape	Param#
Inception_Resnet_V2 (Functional)	(None, 9, 9, 1536)	54336736
Sequential_1	(None, 9, 9, 1536)	0
Conv2D	(None, 9, 9, 64)	884800
Conv2D	(None, 9, 9, 64)	36928
Conv2D	(None, 9, 9, 64)	36928
Batch_Normalization	(None, 9, 9, 64)	448
Global_Average_Pooling	(None, 64)	0
Dropout	(None, 64)	0
Dense	(None, 2048)	133120
Dense	(None, 1024)	2098176
Dense	(None, 3)	3075

Total Parameters : 57, 530, 211
Trainable Parameters : 3, 193, 155
Non-trainable Parameters : 54, 337, 056

Figure 5. Proposed model with transfer learning

5. RESULTS AND DISCUSSION

We have achieved 99% training accuracy and 98.2% testing accuracy. The optimal epochs used in this experiment are 10. ‘Adam’ optimizer is used with early stopping criteria. The graph shown in Figure 6 represents epochs vs training and validation losses. The confusion matrix was obtained for 180 testing images. Out of 180 images, one image of the gond class and three images of the Warli class were misclassified as shown in Figure 7.

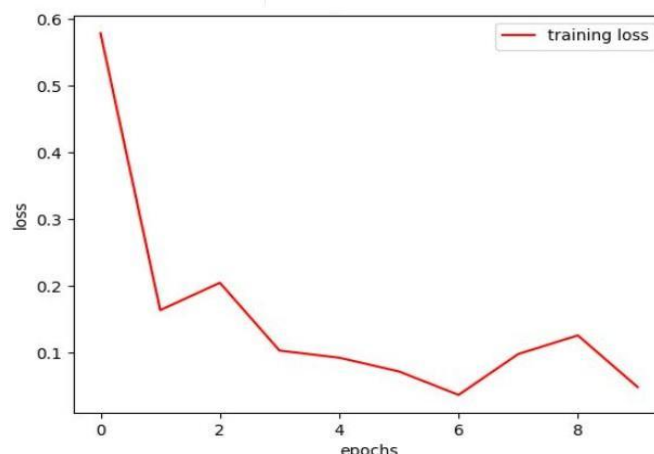


Figure 6. Training loss for 10 epochs for inception ResNet V2 with transfer learning

Figure 8 presents the misclassified images identified in the testing phase. Each subfigure corresponds to an artwork incorrectly labeled by the model, helping analyze the visual attributes contributing to misclassification. Figures 8(a)-(d) illustrate these cases across Gond, Warli, and Manjusha categories.

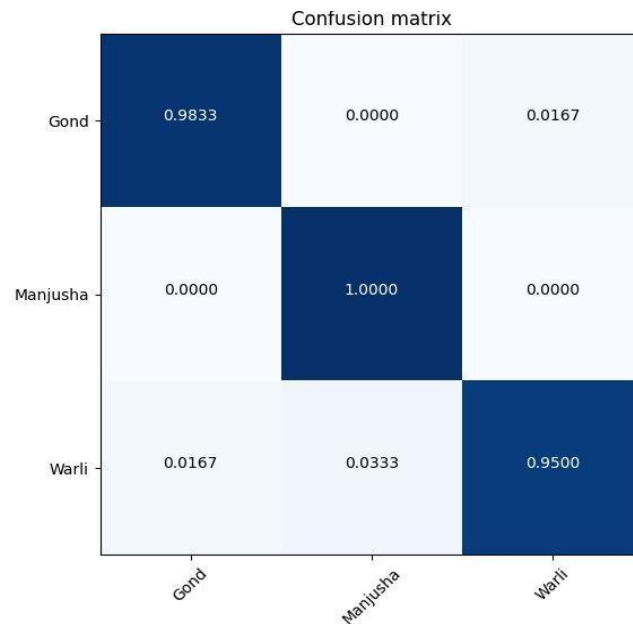


Figure 7. Confusion matrix of testing dataset

Figure 8(a), which belongs to class ‘Gond’, is misclassified as ‘Warli’. Figures 8(b)-8(d) belong to class ‘Warli’. Figure 8(b) is misclassified as ‘Gond’ while the remaining two images are misclassified as ‘Manjusha’. In Figure 8(a), as we zoom in, even though it contains lots of small ‘*’ and straight lines, it creates an illusion of geometric shapes such as triangles and circles. That may have triggered the misclassification as ‘Warli’. In Figure 8(b) the Warli characters are in the center while the prominent area has no details of the Warli art form. The colors are used heavily for the demonstration of different festivals in Gond paintings. The same is present in Figure 8(b) leading to the misclassification as Gond instead of Warli. Figure 8(c) has shades of green colour in the majority of the image area. It is a highlighting feature of the Manjusha art form. This could be the reason for the misclassification. Same for Figure 8(d) it is abundantly yellow, one of the heavily used colours in the Manjusha art form.



Figure 8. Misclassified images; (a) gond, (b) Warli, (c) Warli, and (d) Warli

6. CONCLUSION

This study proposed a deep learning-based framework for the automatic classification of three Indian tribal art forms using transfer learning on the Inception-ResNet-V2 architecture. A manually curated dataset of 900 images was expanded using data augmentation, enabling the model to achieve a high testing accuracy of 98.21%. These results demonstrate the effectiveness of deep learning for distinguishing visually similar traditional art forms.

Beyond performance, the findings contribute to cultural informatics by providing a baseline dataset and methodology for tribal art classification. However, the study is limited by dataset size, class imbalance risks, and reliance on 2D image variations. Future research may extend this work by expanding the dataset, exploring generative augmentation (GANs), integrating explainable AI methods to highlight decision regions, and developing mobile applications to support real-time art recognition and education.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization

M : **M**ethodology

So : **S**oftware

Va : **V**alidation

Fo : **F**ormal analysis

I : **I**nvestigation

R : **R**esources

D : **D**ata Curation

O : Writing - **O**riginal Draft

E : Writing - Review & **E**diting

Vi : **V**isualization

Su : **S**upervision

P : **P**roject administration

Fu : **F**unding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

DATA AVAILABILITY

Data availability does not apply to this paper as no new data were created or analyzed in this study.

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