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Utilizing Deep Learning Techniques to Identify People by Palm Print

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ABSTRACT

Person recognition systems have been applied for several years, as fingerprint recognition has been experimented with different image resolutions for 15 years. Fingerprint recognition and biometrics for security are becoming commonplace. Biometric systems are emerging and evolving topics seen as fertile ground for researchers to investigate more deeply and discover new approaches. Among the most prominent of these systems is the palm printing system, which identifies individuals based on the palm of their hands because of the advantages that the palm possesses that cannot be replicated among humans, as in its theory of other fingerprints. This paper proposes a biometric system to identify people by handprint, especially palm area, using deep learning technology via a pre-trained model on the PolyU-IITD dataset. The proposed system goes through several basic stages, namely data pruning, processing, training, and prediction, and the results were promising, as the system's accuracy reached 90% based on the confusion matrix measures.

Keywords: Palm print, Security, Biometric, Deep learning, Dataset.

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استخدام تقنيات التعلم العميق للتعرف على الأشخاص من خلال طباعة الكف

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الخلاصة

نظام التعرف على الاشخاص تم تطبيقها من عدة سنين حيث تم تجربة التعرف على بصمات الأصابع بدرجات دقة مختلفة للصور لمدة 15 عامًا. أصبح التعرف على بصمات الأصابع والقياسات الحيوية للأمان أمرًا شائعًا. تعد أنظمة القياسات الحيوية موضوعات ناشئة ومتطورة يُنظر إليها على أنها أرض خصبة للباحثين للتحقيق بشكل أعمق واكتشاف مناهج جديدة. ومن أبرز هذه الأنظمة نظام بصمة الكف ، الذي يحدد الأفراد بناءً على راحة أيديهم بسبب ما تمتلك راحة اليد من مميزات غير قابلة للتكرار بين البشر كما في نظريتها من البصمات الاخرى . تقترح هذه الورقة نظامًا بايومتري لتحديد الأشخاص من خلال بصمة اليد ، وخاصة منطقة الكف ، باستخدام تقنية التعلم العميق عبر نموذج مدرب مسبقًا على مجموعة بيانات PolyU-IITD. حيث يمر النظام المقترح بعدة مراحل اساسية وهي تشذيب البيانات والمعالجة والتدريب والتنباء و كانت النتائج واعدة ، حيث وصلت دقة النظام إلى 90٪ بناءً على مقاييس مصفوفة الارتباك.

الكلمات المفتاحية: البصمة ، الأمن ، البيومترية ، التعلم العميق ، مجموعة البيانات.

1. INTRODUCTION

Palm print recognition systems use scanning equipment or a camera-based application and supporting software to process image data from a photograph of a person's palm and match it to their previous record **(Ali et al., 2018)**. Palm prints share information with fingerprints. Palm scanners, like fingerprint scanners, use optical, thermal, or tactile technologies to reveal a human palm's ridges, bifurcations, scars, wrinkles, and texture **(Veigas and Kumari, 2022)**. These approaches use visible light, heat-emission analysis, and pressure analysis. Palm scanners can be touch-based or contactless. Palm prints and fingerprints are often combined to improve identification **(Hussien and Abdullah, 2023; Ungureanu et al., 2020).** Because a handprint covers more skin areas, it contains more identifiable characteristics, making false positives nearly impossible and purposeful falsification more complicated **(Poonia et al., 2020).** When fingerprints are lacking, criminal investigations may use palm prints. Palm prints are little areas of the palm surface that contain more information for person identification systems **(Bachay and Abdulameer, 2022; Al-Zwainy and Hadal, 2016)**. It has a distinct trait and is permanent because it does not change. Palm prints, unlike fingerprints and faces, are reliable and safe Palm prints vary **(Zhong et al., 2019; Hafeez et al., 2020).** Ridge bifurcation and termination are fingerprint line minutiae characteristics. Geometry, Delta point, significant lines, and wrinkles are other features. Different methods extract these traits **(Kong et al., 2009; Mohsen et al., 2021)**. Palm printing has no adverse effects because low- and high-resolution technologies can capture this property. Another benefit is its small size and high acceptance rate **(Aberni et al., 2017).** Many previous studies discussed this topic **(Attallah et al., 2019; Zhang et al., 2023).** The approach in **(Ungureanu et al., 2020; Minaee et al.,**

2023) was based on the combination of spiral features and LBP filters, with mRMR used to select the optimal features. The feature extraction process begins by dividing the image into segments, followed by skew. The kurtosis is computed for each block before calculating the VECTOR feature using the spiral method and for the K-Nearest Neighbor (KNN) classification. Applying the technique to handprint images from three databases **(Poonia et al., 2020; Ajagbe and Adigun, 2024).** Delaunay Triangle Internal Angle was offered as a palmprint template based on the local geometry of minute features for palmprint recognition. Delaunay triangulation resists local disruptions mathematically. The template generates minutiae triplets using the minutiae transform method. These triplets also provide interior angles and prototype handprint matches. The proposed template resists palmprint rebuilding: rotation, translation, and distortion-invariant pattern. The proposed method improves Correct Recognition Rate (CRR) on PolyU, IIT-Delhi, and Multispectral palmprint datasets **(Kadhm et al., 2021; Soares et al., 2020).**
The model includes preparation, ROI extraction, and hybrid AE+CNN feature extraction and matching. The COEP palmprint database has few photos, making training deep learning models that need many images challenging. Artificial intelligence plays a significant role in developing systems worldwide, leading to the urgent need to develop previous strategies and discover modern systems that address previous errors **(Al-Taie and Khaleel, 2023; Yousif and Ali, 2020)**. The evolution in the field of Artificial Intelligent (AI) with its training algorithms makes AI very important in different aspects of life **(Amrouni, 2023).** This work proposes a biometric system to detect people through the palm based on deep learning methods, especially the pre-trained model, with preliminary processing operations. The work was done on data containing different and varied conditions that could affect the diagnosis, such as tattoos, henna, writing, burns, deformities, and other conditions.

2. THE PROPOSED SYSTEM

The proposed system is based on using a pre-trained module, which is ResNet-50, and processing operations. **Fig. 1** shows the steps of the proposed approach.

2.1 Dataset

Indian and Chinese volunteers collected this database. The initial joint database was collected using several sites' general-purpose hand-held cameras. To our knowledge, the most excellent palmprint database was collected over several years from over 600 subjects. This database offers left- and right-hand photos for each issue. Thus, this database's images are subject-based and vary widely. Each topic has 20 photos spanning 5–72 years. Non-officer workers, farmers, agricultural laborers, damaged palms, and hands with special abilities or injuries were studied. This database's palmprint picture samples, obtained over 15 years, are unique. Researchers can download this paid data set by mailing the site **(Fei et al., 2020)**. **Fig. 2** shows the dataset split in the proposed system, i.e. the ratio between testing and training that was divided based on (8.1.1), which means eight equal training, one equal testing, and another equal evaluation.

2.2 Data Pruning Step

This dataset contains three critical files (the original, the grayscale, and the segmentation). Moreover, upon downloading and working on this dataset, the following point facts were discovered that previous researchers had not made clear:

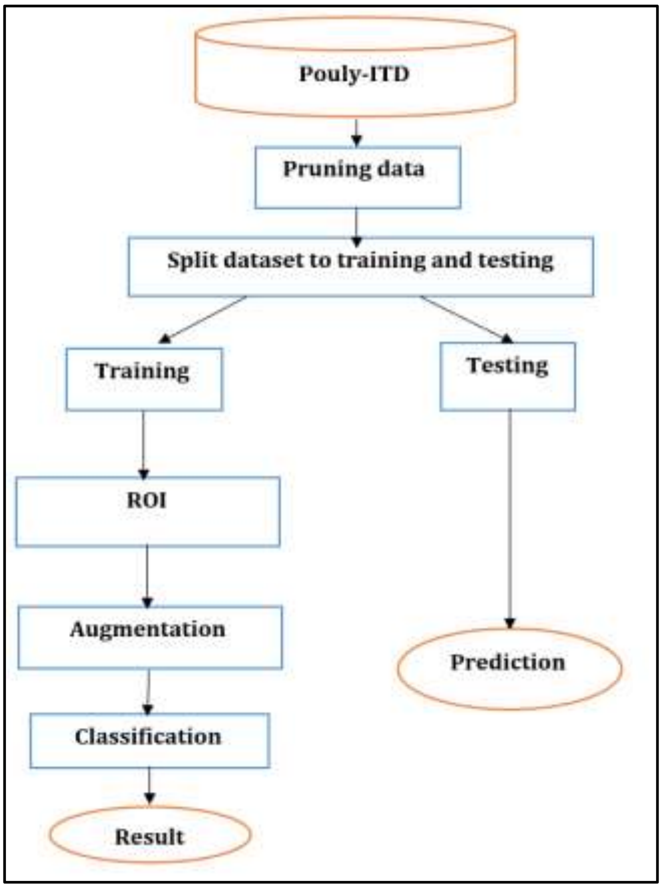

Figure 1. Block diagram of the proposed system

1) The original file is an image without processing or trimming, and its size is (9.626 GB). This size is considered relatively large as a single image (712KB), which means its dimensions (1280*960) are significant for training and consume very high training time.

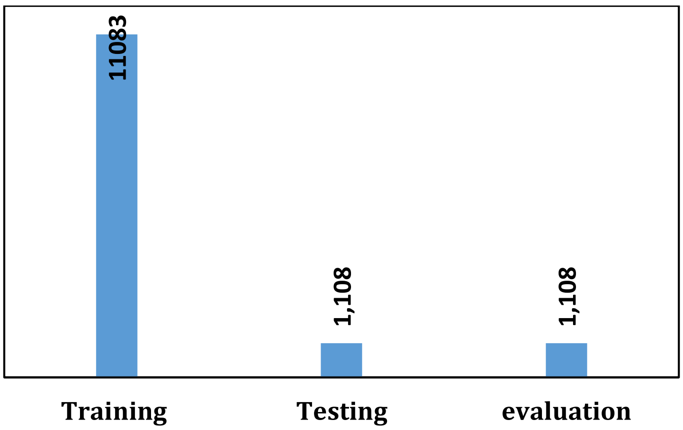

Figure 2. Split dataset (POLYU-IITD) in the proposed system.

2) A segment file is what is meant by ROI, and it is colored, and its sizes are variable and not fixed, as the size Original (9.6263 GB), Segmentation (ROI=69.7MB). The grayscale file had unsuitable dimensions, 128 * 128, which is very small compared to the original. It was presented by the designers of the data set as a challenge for researchers to work on images of minimal and unclear size. Unfortunately, this challenge is not helpful because the image produced by the recognition devices by the palm print is Very accurate. **Table 1** describes the details of PolyU-IITD **(Liu and Lang, 2019)** and why choosing a second folder (segmentation) in the proposed system.

Table 1. Different types of folders in the PolyU-IITD dataset.

Type	Size	Dimensions
Original	9.626 GB	1280*960
Segment	69.7 MB	Variable
Grayscale	47.6 MB	256 * 256

The problem is that this data was arranged in a problematic way to train because of merging the images of the right hand with the left. Therefore, a pruning process was completed by arranging the folders, where each person has two folders (0) and (1), meaning the right and left hand, meaning the number of folders has become 617. This is a crucial pruning process to make a prediction correctly. **Table 2** describes of PolyU-IITD dataset with pruning.

Table 2. Description of PolyU-IITD dataset with pruning.

Property	Value
Size	72.2M
Person	611
Image	For each person, two session 10=Right Hand 10=left hand
Total image	12,220
Type	RGB
Dimension	Variable

2.3 Resizing Step

Due to the different image sizes resulting from the ROI process, this difference causes oscillation in the training process. Therefore, the second treatment step in the proposed second system model is standardizing the image sizes. The process of standardizing image sizes, and the size was (256 * 256) based on experiments, and **Table 3.** explains the reason for choosing the size (256 * 256) in model two.

Table 3. Size standardization experiments

Type	Size	Training Time	Training accuracy
Resizing (1)	128*128, 47.6 MB	~10 hours	81%
Resizing (2)	256*256, 72.2 MB	~12 hours	86%
Resizing (3)	512*512, 320 MB	~15 hours	87%

The above Table shows that the (resize) process has become the size of the entire data set, 2.72 MB. In contrast, its original size was 9.6263 GB. For this reason, the ROI file was chosen, as the output of image size standardization was beneficial for the proposed system in data processing. The benefit of both was to reduce the training time and obtain high-accuracy results. The main goal is to maintain the features the model will produce and train. Where notice the difference between the two sizes (256 * 256) and the size (512 * 512) is one in a thousand in accuracy, but at the time of execution, (256 * 256) was the fastest, and therefore its choice was the best. Where size (128 * 128). The implementation time was the least, but in terms of accuracy, it is the least, and the results are unsatisfactory. In a proposed system using the operation of resampling with resizing, the benefit of this step is to preserve the highest number of features in the single image, that is, to help obtain a high-resolution image. Where this method was adopted in the proposed system based on experience, and accordingly, it was chosen (Lanczos). Resampling is typically used to increase a digital signal's sampling rate or shift it by a fraction of the sampling interval. For example, it is often used for multivariate interpolation to resize or rotate a digital image. This work considered it the "best compromise" among several simple filters.

2.4 Data Augmentation Steps

This process is entirely similar to what was explained in the first model in all its details. Noting that the process of training the model on hypothetical cases is not available to deal with the most significant number of problems that may affect the recognition process, and these default problems that are made on the images are related to the training part only to conduct effective and accurate training and to improve the stability of the model. **Figure 3** describes the example of AugMix in the proposed system (PolyU-IITD) data set. **Table 4.** shows how AugMix was affected in the proposed approach in part training only.

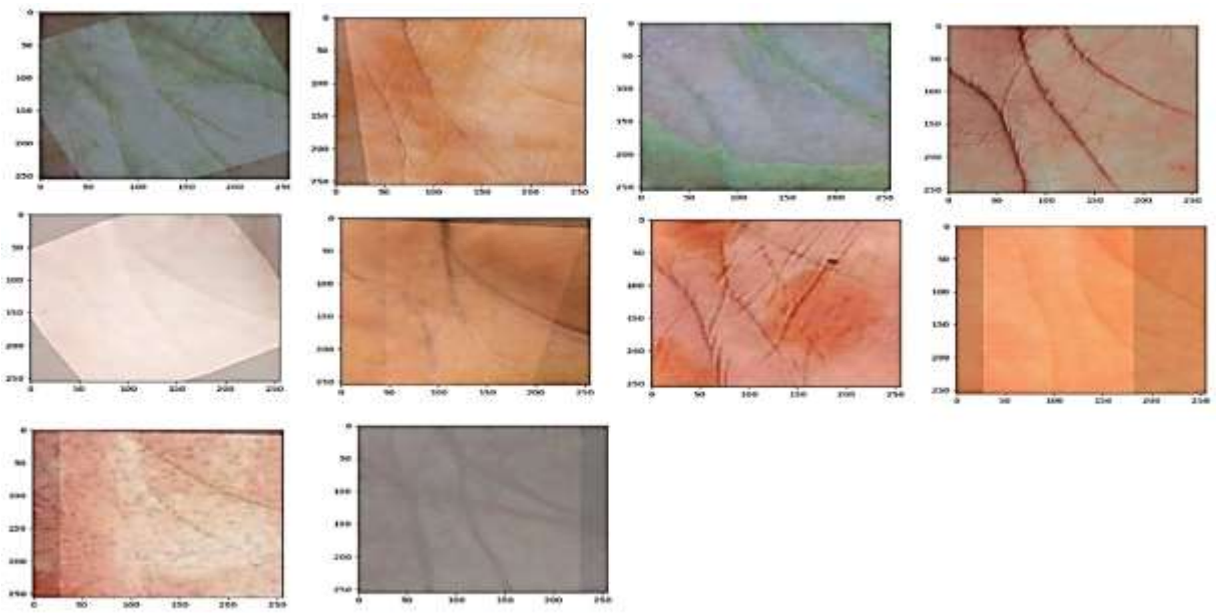

Figure 3. Example of AugMix in the proposed system (PolyU-IITD) data set.

Table 4. Effected AugMix in the proposed system in the cope dataset

Type	Accuracy of training	Time of training
Without augment	86%	~12 Hours
With AugMix	88%	~14 Hours

3. TRANING MODEL

Both a convolutional neural network with 50 layers and a convolutional neural network with 50 layers are included in ResNet-50. (48 layers of convolutional data, one layer of MaxPool data, and one layer of intermediate pool data) **(Htet and Lee, 2023; Ghadi and Salman, 2022)**. The layering of residual blocks forms the artificial neural network (ANN) type known as residual neural networks. Because of the structure of the trained model, the 50-layer ResNet in the proposed system uses a bottleneck design for the building block. This is because the ResNet was trained on the ResNet-50. Using 11 convolutions, often known as a "bottleneck," a residual bottleneck block can reduce the number of parameters and matrix multiplications needed. Design and implement Neural Network **(Al-Rubaye et al., 2020; Al-Jamali, 2020)**. The training of each stratum is greatly accelerated as a result of this. Furthermore, it uses an array with three layers instead of two levels. The best (ANN) performance was the sigmoid function as the coefficient of correlation **(Hussein and Al-Sarray, 2022; Kheder and Mohammed, 2023)**. ANN model was used for predicting **(Abbas et al., 2019f; Soares and Angelov, 2020).** Moreover, all of this may be summed ResNet50 and looking at **Fig. 4,** which is as follows:

- 7*7 Kernal convolution alongside 64 other Kernal with a 2-size stride.
- A max pooling layer with a 2 _2-sized stride.
- 9 more layers (3*3,64 kernel convolution, another with 1*1, 64 kernels, and a third with 1*1 ,256 Kernal). These three layers are repeated three times.
- 12 more layers with (1*1 ,128 Kernal ,3*3, 128 kernel, and 1*1,512 Kernal) iterated 4 times.
- 18 more layers with (1*1 ,256 Kernal, and 2 Kernal 3*3 ,256 and 1*1 ,1024 Kernal) iterated 6 times.

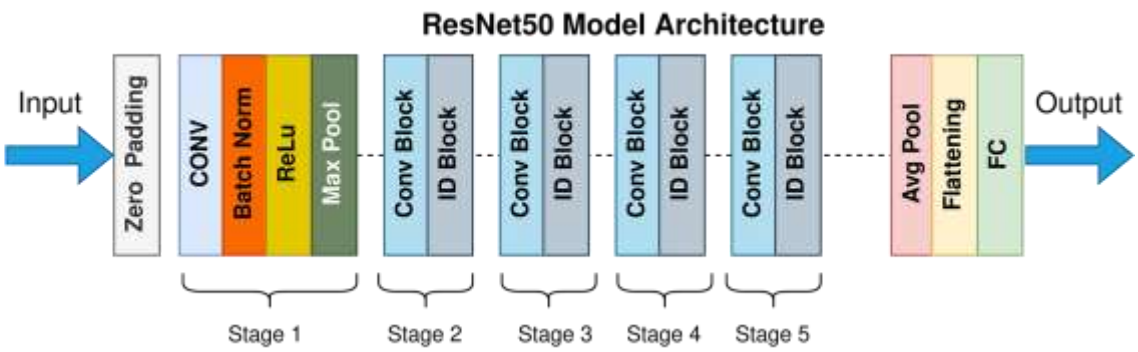

Figure 4. Summarized layer in resent 50.

4. RESULTS AND DISCUSSION

Evolve this model by measuring confusion matrices **(Abood and Al-Jibory, 2023; Zhao et al., 2019**). This measure has a standard parameter; replacing it with the confusion matrix measures get the results of the values, and these values will be reviewed in two ways **(Mahmood and Hameed, 2023)**, with the presence of augmentation data and the lack of them, to show the importance of this step. **Table 5** shows the stander parameter results. **Figures. 5** and **6** show the difference between the results.

Table 5. Result of the model with augmentation and without.

Without augmentation		With augmentation	
TP (true positive)	514	TP	520
FP (False positive)	81	FP	72
FN (False Negative)	96	FN	77
TN (True Negative)	531	TN	553

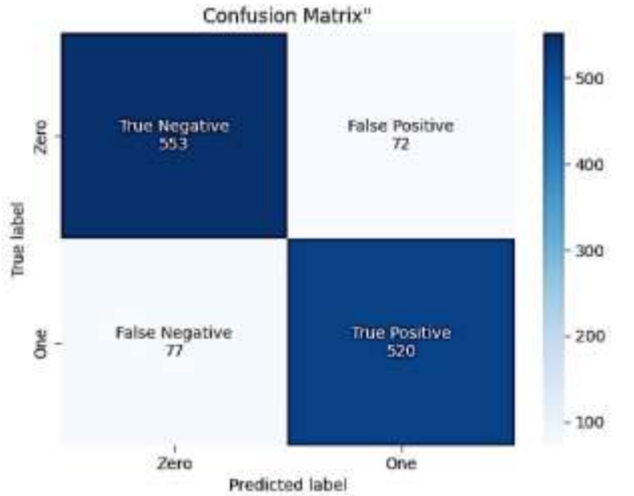

Figure 5. Confusion matrix in model with Augmix

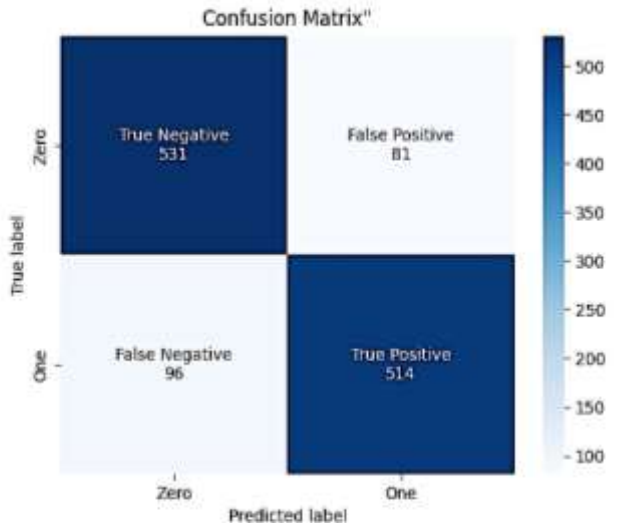

Figure 6. Confusion matrices in model without Augmix**.**

where:
TP is the True Positive, TN is the True Negative, FP is the False Positive, FN is the False Negative.
The confusion matrix is a valuable tool for assessing a classification model's performance and learning more about the kinds of mistakes it commits. Several significant metrics can be computed from the confusion matrix, and it is included. **Table 6** shows the system result based on the Confusion matrix and summarizes the result of the model when not using augmentation in the training model.

Table 6 Result of metrics in confusion matrices in the model

Result of the model without augmentation		
Precision	Recall	F1
0.863	0.847	0.854
Accuracy = 86%; and ERR=0.14		
Result of the model with augmentation		
Precision	Recall	F1
0.881	0.875	0.877
Accuracy = 88% and ERR=0.12		

Precision= TP/TP+FP; Recall= TP/TP+F; F1=2* Precision* Recall/ (Precision + Recall)

5. CONCLUSIONS

The biometric system is an integral part of life's wish because of the large number of events that led people to think about ways of security authentication, and these methods went through many stages of passing through the fingerprint, the iris of the eye, the face, the electrocardiogram, and other ways. The biometric system in this work was made on a distinguished global data set. The difficulty of working on it, and most of the previous researchers resorted to extracting the measure of the error rate only in it to adopt it and consider it a challenge to work on it and extract all the measures that qualify the researchers to evaluate it. The work went through primary stages, namely pruning the data, processing it, classifying it, and evaluating it using the confusion matrix, where the results were good and as future works, the integration of these data was grouped with another group to cover most cases that affect identification, such as tattoos, henna, wounds, diabetes, and other conditions**.** This proposed method, through the preliminary processing operations with the classification process in the pre-trained model method, had promising results, and the refinement process is to include all cases of the global data set and to review the work with the results for all possibilities. A suggestion for future work is to work on manually collected data in a way that logically simulates reality.

NOMENCLATURE

Symbol	Description	Symbol	Description
DL	Deep Learning	LBP	Local Binary Pattern
ERR	Error Rate Ratio	ROI	Regin Of Interest
FP	False Positive	TN	True Positive
FN	False Negative	TN	True Negative

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Credit Authorship Contribution Statement

Alyaa Al-Barrak: Supervisor, editing, developing the data processing process.
Mathiq Hasan: Conducted the data collection, application of the data processing process, writing the manuscript, editing and revise the text.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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