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A Deep Learning Algorithm Grounded Image Dehazing for Corrupted Underwater Image Classification

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Abstract: Salt marshes, coral reefs, the deep sea, and the seafloor are all parts of the marine ecosystem, which is the largest of Earth's aquatic ecosystems. The low quality of photographs captured underwater due to a number of degradations, however, has prevented this potential from being fully realised. The current research sheds insight on common issues with underwater images, such as colour shift, haze, dim lighting, uneven lighting, and poor contrast. When the blue colour wavelength is not absorbed in seas of sufficient depth, it typically leads to a bluish colour cast, which degrades underwater photographs. As a result, the colour information in marine photographs is compromised. The Colour Corrected single-scale Retinex (CCSSR) approach is used to color-correct underwater photographs, and the proposed work focuses on characterising the various ranges of the colour cast present in such photos. Additionally, an illumination enhancer helps bring out more detail in the underwater photo. Natural Image Quality Evaluation (NIQE), Blind/Referenceless Image Spatial Quality Evaluator (BRISQUE), Underwater Image Quality Measure (UIQM), and entropy are only some of the non-reference quality measures used to assess the quality of the work that has been proposed. When compared to underwater images processed using the Automatic Red Channel Restoration (ARCR) method, the entropy of the proposed DCP MSR-based fusion is 24.2% higher, and the UIQM is 34.25 percentage points higher.

Keywords*: *CCSSR; NIQE; UIQM; ARCR; DCP.

1. Introduction:

As one of the few remaining uncharted regions on our planet, the ocean and other bodies of water are a fascinating frontier. These uncharted places, however, won't stay that way for long, thanks to technological breakthroughs like remotely controlled underwater submersibles and the growing desire to extract various resources. The underwater imaging model created by Jeffy-McGalmey is shown in Figure I. The sum of the image's direct, forward, and backscattered light is what reaches the camera. The particles in the camera's path cause forward scattering because of the local light's internal reflections off of each other [1]. The image's low contrast is caused by backscattering, which is generated by the reflection of light owing to turbidity; the degree of the deterioration increases with turbidity.

The intensity of scattering is said to be inversely proportional to the fourth power of wavelength, as proposed by the Rayleigh scattering hypothesis. Thus, shorter-wavelength colours scatter more dramatically than longer-wavelength ones [2]. Hence, underwater photography tends to turn out looking blue because the greater red wavelength is attenuated at a faster rate than the shorter blue wavelength.

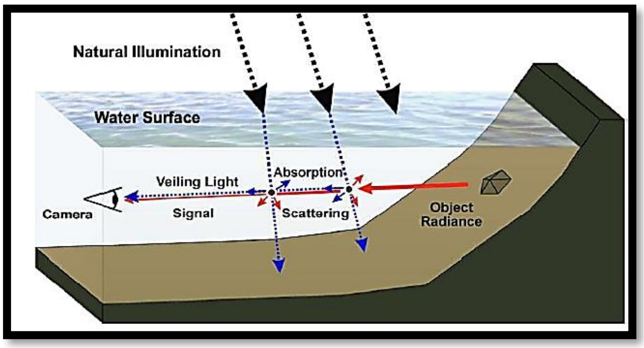

Fig I: The underwater imaging model. [Google]

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1.1. Haze:

Atmospheric absorption and scattering create a phenomenon known as haze. The underwater hazy image formula is given by:

$$I(x) = J(x) * t(x) + A(1 - t(x)) \quad (1)$$

Where, I is the measured brightness, J is the radiance of the scene, t is the transmission of the medium, and A is the global atmospheric light, representing the proportion of the incident brightness that was not dispersed and reached the camera.

1.2. Colourcast

A colour cast is an unintended change in hue that appears in a photograph. Because blue light travels farther than green or red light through water, underwater photographs often take on a bluish hue [3].

1.3. Low Contrast

The contrast between an image's bright and dark areas is what makes it stand out. High-contrast images are characterised by striking contrasts in light and shade, saturation, and texture. Low-contrast images may appear flat or lifeless due to a limited tonal range. The lack of significant contrast between dark and light areas in an image causes it to appear flat.

1.4. Low Illumination

The acceptable visible light energy on a unit area is what we mean when we talk about illumination. Luminous flux, or Lux.

1.5. Non-Uniform Illumination

Because natural light is lost due to absorption, artificial light sources are commonly connected to underwater vehicles. Yet, sometimes the light from these flashlights isn't distributed evenly, leaving a bright patch in the middle of the picture and a dark area on each side of it.

Due to growing interest from both the military and the general public, underwater imaging has emerged as a promising new field of study. In many situations involving the ocean floor, such as surveys of coral reefs, the counting and monitoring of marine organisms, pipeline maintenance, underwater mines, shipwrecks, etc., continuous monitoring is required [4]. It's true that we've mapped out every inch of Mars, the Moon, and other planets, but we've just scratched the surface of the ocean on Earth. 1, 2 As a result of low light levels and the need to descend hundreds of metres to reach the sea floor, this is the case. In recent years, scientists all over the world have been able to conduct a wide variety of ocean-related studies by sending remotely operated vehicles (ROVs) and autonomous underwater vehicles (AUVs) to the ocean floor. The photos captured by ROVs every day are massive, and it is becoming increasingly difficult to accurately categorise the various items visible in them. Automated, image processing-based object detection systems are crucial for marine scientists [5]. This is due to the fact that manual classification is both time-consuming and resource-intensive. For practical object classification, a wide variety of image processing methods are at your disposal.

So, the use of artificial intelligence is required to overcome these obstacles and improve classification accuracy. For the first time, there is an intelligent system available for identifying objects in marine photography. The ocean is a largely untapped resource with several potential military, scientific, industrial, and even civilian uses, many of which have yet to be discovered. Since it is dangerous to risk one's life diving many miles into the ocean, the expense of sending humans there has remained high [6]. In order to lessen the difficulty and expense, engineers are working on autonomous systems like remotely operated vehicles (ROVs) and autonomous underwater vehicles (AUVs).

Cameras fitted inside AUVs allow for underwater photography. The recent rise in I the usage of ocean resources and (ii) the sophistication of oceanographic tools has boosted the profile of ocean research [7].

Many investigations, such as those aimed at detecting oil spills, tracking the effects of pollution as a result of rising temperatures, studying the dynamics of coral reefs, tracking the decline of marine life, and searching for extinct species, have fuelled the push to create novel applications for underwater image processing [8].

2. Related Work Done:

Low visibility in underwater photos is due to absorption and scattering, which causes haze and other restrictions. Dehazing is a technique used to restore clarity to blurry photos. Recovery of corrupted information from a hazy image is the main goal of underwater image dehazing methods.

The assumption that one of the colour channels will tend towards 0 in terms of image intensity lies at the heart of Dark Channel [9]. From the initial image, the dark channel is created, and from there, the ambient light and transmission map are saved. A clear picture is then derived from the transmission map after additional processing has been done. Even though they borrow from the framework established by the researchers, the techniques used in the sequels are distinct from the originals.

Dehazing methods that use the Dark Channel Prior (DCP) measure the hazy image's dark channel. Most standard approaches employ a local patch size of 3x3, as increasing the patch size necessarily results in a reduction in dark channel resolution. The authors take the value of the darkest channel to be the amount of light in the atmosphere [10]. Atmospheric values are determined by taking the lowest entropy value from the top 1% of the greatest intensity value in the dark channel. Authors estimate the transmission map using the soft mapping interpolation technique.

The deteriorated image's V channel in the Hue, Saturation, Value (HSV) colour space is adjusted using adaptive histogram equalisation (AHE). A transmission map is generated by applying the morphological filter to the R-channel of Red, Green, Blue (RGB) colours, and then using the guided filter. The underwater image is contrast enhanced and White Balanced (WB), and then the two images are combined to create a dehazed image from which weight maps are extracted [11]. Features related to haze are detected and processed automatically by the Deep Transmission Network (DTN). DehazeNet is a convolutional neural network (CNN)-based back-to-back solution for medium transmission estimation. The authors combine hazy photos and WB images for light estimate and transmission map estimation, fusing the images at each level to improve the edges, salient regions, and saturated areas, thus minimising the image haze, with the use of the Multi-Scale Fusion (MSF) approach [12].

Principal Component Analysis (PCA) was employed by the team of researchers to create this visual. The method uses a nonlinear colour correlation and restoration technique to fix the hue layer. The method incorporates elements of both automatic and human colour recovery [13].

The authors add updated versions of the Retinex White Patch (RWP) into a retinex-based colour restoration algorithm to fix the colours in the photos. Color correction strategies that rely on Single-Scale Retinex (SSR) also exist. In order to merge the RWP and GW algorithms, an Automatic Color Equalization (ACE) technique was used [14]. Later, this method was revised to offer a new framework for coordinating the colours in several frames with distinct colour deterioration factors.

The S and V components of an image are improved by transforming it from RGB space to HSV using a filter based on the Just Noticeable Difference (JND) metric. The enhancement is employed when assuming white light. Subtracting a portion of the log signal of illumination from the final image V after applying the JND-based filter [15-18]. As a next stage, histogram modelling is applied to V, and the S component is fine-tuned to match V. Finally, after the V and S components have been improved, the full RGB image is constructed [19]. The JND-based nonlinear filter is applied to the image, and the reflectance is estimated, only the V component is changed. Following this, estimations are subjected to Gamma Correction (GC), and an improved RGB image is constructed using the original H, S, and the corrected V components. When compared to the prior algorithm, this one produced superior outcomes [20-22].

Authors introduced the Multi-Scale Retinex (MSR) as a weighted sum of multiple SSR outputs. The MSR method made an effort to convey a real-world application of the retinex without requiring human validation of an image [23-24]. To produce an output image with a graceful rendition free of halo artefacts, the most important constraint is to choose the optimal number of scales based on a wide variety of parameters and constraints. The authors analysed the compromise between faithfulness to the source material and dynamic range compression, both of which are constrained by the ambient space constant. It was originally discovered that the standard retinex methods caused halo artefacts. As a result, the contrast between adjacent areas of the same colour was diminished [25].

3. The Objective of the Research Work:

The study aims to answer the following questions:

1: Collect elements mostly used for deterioration-based classification of underwater photos.

2. To categorise underwater photographs based on their degradations considerably faster and more accurately than alexnet with the use of a newly designed architecture.

3. We want to develop a straightforward method to enhance the scene's legibility in a variety of underwater photographs.

4. The fourth objective is to create a system that can analyse the degree to which an underwater image has been impacted by colour cast, and then restore that image.

4. The Proposed Work:

Both the DCP and MSR procedures were independently used to the degraded image of the undersea scene. After that, the resulting pictures are combined by using a DCP MSR-based fusion that was proposed. The DCP technique is applied in this work because it improves the contrast of the underwater photographs. Despite this, the technique does not result in an increase in the images' overall luminance. Because the DCP algorithm considers the top 0.1% of the brightest pixels to be air light-medium, hazy photos that have been processed by the DCP often have a halo appearance. In order to get rid of the halo effect, the output images that were obtained through processing the DCP and the output images that were obtained via processing the MSR approaches are mixed. The MSR was able to maintain a good amount of brightness, which resulted in an improvement across the board in the underwater photos. The MSR technique's most significant shortcoming was that the underwater images it produced were over-illuminated. During the DCP MSR-based fusion procedure, the excessive lighting was corrected so that it is now balanced.

The output images that are referred to as DCP out and MSR out respectively are those that were obtained through the DCP and MSR procedures. The output pictures that have been produced in this manner are then further fused utilising the suggested DCP MSR based fusion, where the approximation details of DCP and MSR were located in A1 and A2, respectively. B1, C1, and D1 contained the horizontal, vertical, and diagonal details of the DCP and MSR, while B2, C2, and D2 contained those details, respectively. The fusion of the DCP and MSR outputs was carried out in the manner shown in the Figure II that follows.

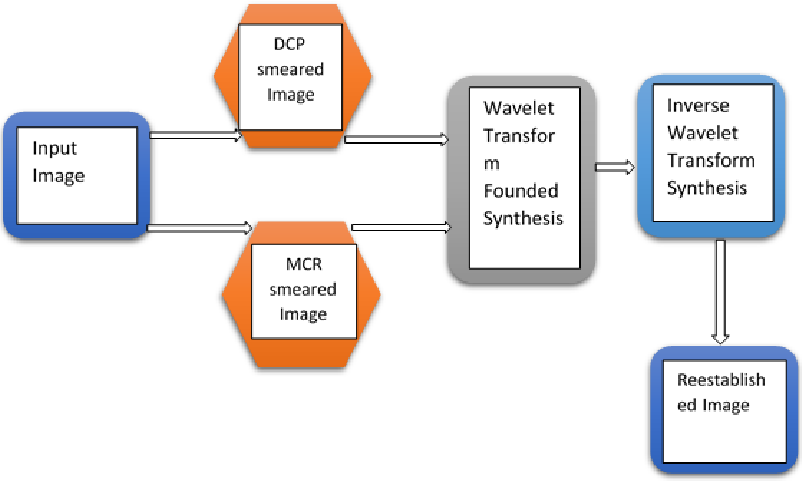

Fig II: The Proposed Block Diagram.

However, the method does not improve the overall brightness of the photos. Halos are a common feature of DCP-processed hazy photographs because the DCP algorithm treats the top 0.1% of brightest pixels as air light-medium. Combining DCP and MSR processed output photos eliminates the halo effect. In general, the MSR's ability to keep a high level of illumination made for better underwater photographs. The MSR method had one major flaw: the underwater images it created were too bright. The excessive illumination was adjusted during the DCP MSR-based fusing process.

5. Result and Discussion:

Underwater photos that have been degraded using the based fusion technique are compared to those that have undergone the DCP and MCR processes. Entropy, the Underwater Image Quality Measure (UIQM), the Natural Image Quality Evaluation (NIQE), and the Blind/Referenceless Image Spatial Quality Evaluator are used to assess the efficacy of the various dehazing methods (BRISQUE).

1.6. Entropy:

The entropy of a picture is a measure of how much data is contained within it. When the entropy value is high, that means there is a lot of variation between adjacent pixels in the image. A unit of entropy cannot be defined. Image entropy is determined by:

$$Entropy = -\sum p \log p \qquad (2)$$

Where, P is Normalized Histogram count.

1.7. Natural Image Quality Evaluator

Mittal et al. developed a quality metric they call the natural image quality evaluator (NIQE) (2013). No Reference Quality Evaluation (NIQE) is an evaluation method in which no external standards are used. NIQE is based on Natural Scene Statistic (NSS), where the features are obtained from natural photographs, and it makes advantage of statistical regularities detected in such photos. Image quality with any distortion can be evaluated, and it is option-blind. Without knowing what kinds of aberrations to expect, NIQE may evaluate an image's quality. Thus, the better the image quality, the lower the NIQE number. There is no measurable NIQE.

1.8. Blind/Referenceless Image Spatial Quality Evaluator

NSS serves as the foundation for the blind/referenceless image spatial quality evaluator (BRISQUE). The NSS calculates potential 'naturalness' losses in a picture as a function of distortions by analysing scene statistics of locally normalised luminance coefficients. As a result, the image appears more genuine. Since lower BRISQUE values indicate higher quality images, this is the case. There is no measureable equivalent to BRISQUE.

Table I: Entropy Value Comparison of proposed method with Existing approaches.

S. No.	Input image	DCP	MSR	DCP-MSR based fusion
1	6.49	7.21	7.41	7.77
2	6.37	7.20	7.35	7.68
3	6.16	7.18	7.31	7.65
4	6.10	7.17	7.28	7.53
5	5.92	7.16	7.25	7.50
6	5.77	7.15	7.21	7.49
7	5.66	7.13	7.20	7.44
8	5.43	7.08	7.11	7.35
9	5.34	6.89	7.01	7.31

The photos processed using the DCP method clearly displayed an increase in artefacts as the level of haze in the original images increased. The MSR method's processed photos are brighter and smoother than their original versions. As evidenced by a number of quality indicators (including entropy, NIQE, BRISQUE, and UIQM), the proposed DCP MSR based fusion successfully removed haze from underwater photos, outperforming state-of-the-art methods. There is a comparison in table I between the MSR, DCP, and DCP MSR based fusion approaches and their respective image quality.

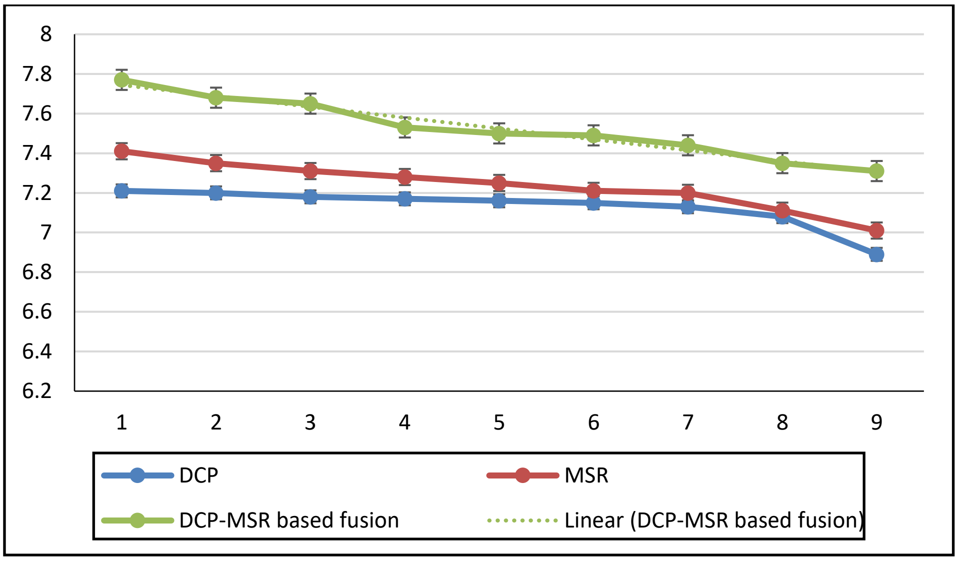

Fig III: Entropy Value Comparison of proposed method with Existing approaches.

The highest average entropy value of 7.44 is found in photos processed using DCP MSR based fusion, which is indicative of the quality of the information contained within the images. Tables II and III list the NIQE and BRISQUE values that reflect how realistic an underwater image is.

Table II: NIQE Value Comparison of proposed method with Existing approaches.

S. No.	Input image	DCP	MSR	DCP-MSR based fusion
1	3.95	4.97	4.18	3.41
2	3.89	4.86	4.67	3.45

3	3.75	4.81	4.79	3.42
4	3.68	4.73	4.75	3.76
5	3.59	4.62	4.61	3.82
6	4.23	4.37	4.45	3.67
7	4.14	4.18	4.19	3.49
8	5.02	5.18	5.28	3.62
9	5.18	5.39	5.40	3.84

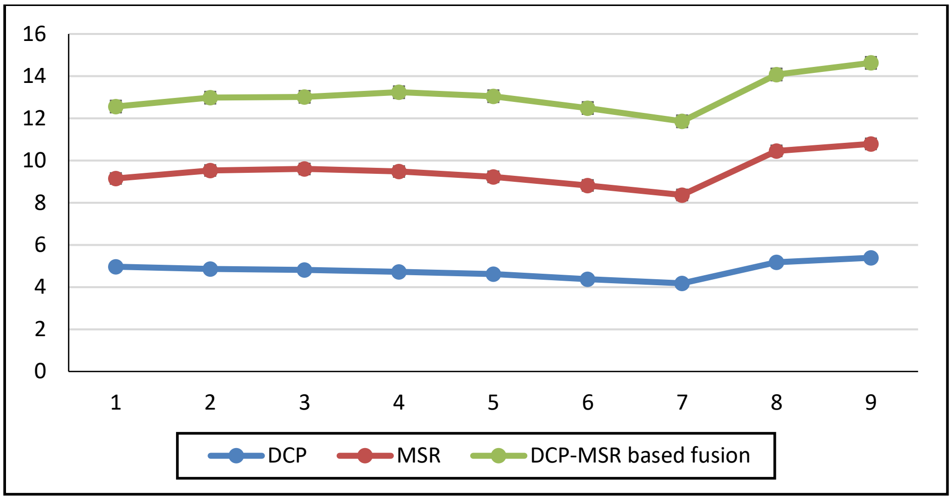

Fig IV: NIQE Value Comparison of proposed method with Existing approaches.

Table III: BRISQUE Value Comparison of proposed method with Existing approaches.

S. No.	**Input image**	**DCP**	**MSR**	**DCP-MSR based fusion**
1	20.45	22.45	20.34	18.61
2	21.59	22.68	20.27	18.25
3	22.49	22.35	20.18	18.34
4	27.41	23.18	21.59	19.27
5	28.59	24.18	23.49	19.62
6	29.15	24.51	23.57	19.27
7	32.29	24.37	24.18	21.19
8	33.67	25.01	24.45	21.37
9	34.62	25.34	24.13	21.30

From table II and III, we can conclude that, losing the naturalness of the images, as evidenced by generally high NIQE and BRISQUE values and the lowest entropy, which indicates loss of information and contrast. While this was not the case with raw underwater photographs, MSR processed images showed a remarkably smooth image.

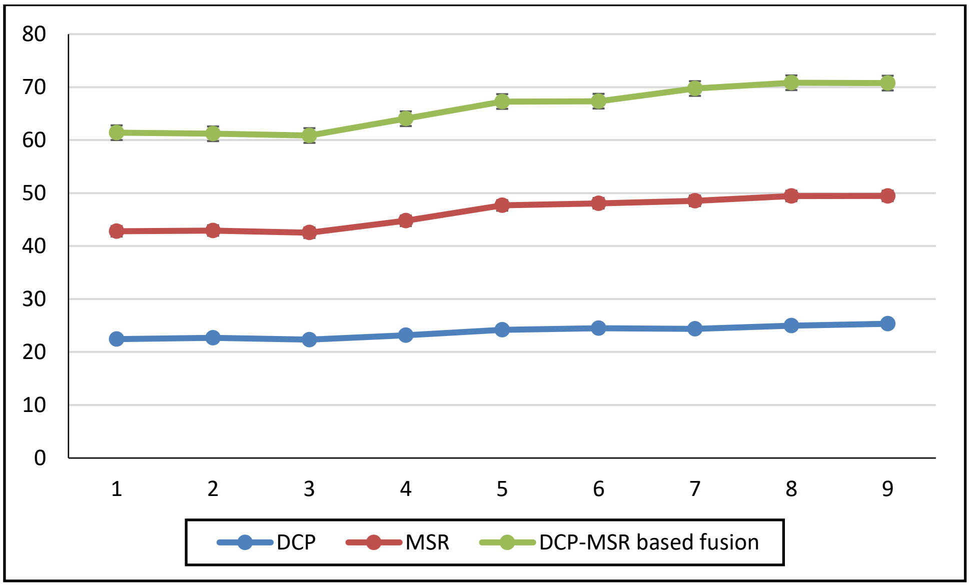

Fig V: BRISQUE Value Comparison of proposed method with Existing approaches.

Also, the suggested DCP MSR based fusion produced dehazed and contrast-enhanced output for underwater images that was superior to that of conventional underwater image dehazing methods. NIQE and BRISQUE were reduced by 55 and 53.06%, respectively, in underwater photos processed using the suggested DCP MSR based fusion, demonstrating that this method successfully preserved the images' naturalness.

6. Conclusion:

Underwater images can be degraded in a number of ways, and this research sheds light on some of them. The categorization procedure relies heavily on feature selection. Salt marshes, coral reefs, the deep sea, and the seafloor are all part of the marine environment, which is the biggest aquatic ecosystem on Earth. Unfortunately, the low quality of photos acquired underwater due to a number of degradations has remained a barrier to its development.

The Colour Corrected single-scale Retinex (CCSSR) approach is used to colour correct underwater photographs, and the proposed work focuses on characterising the various ranges of the colour cast present in such photos. Moreover, an illumination enhancer is used to improve the lighting of the underwater image. Natural Image Quality Evaluation (NIQE), Blind/Referenceless Image Spatial Quality Evaluator (BRISQUE), Underwater Image Quality Measure (UIQM), and entropy are only a few of the non-reference quality measures used to assess the proposed work. DCP MSR based fusion methodology dehazed and improved the contrast and luminance of the underwater photos by combining DCP and MSR methods. Maximum entropy and minimum NIQE and BRISQUE values are displayed by the DCP MSR based fusion method. Hence, in terms of naturalness, contrast, and information retention after processing, it excels above and beyond the state-of-the-art DCP and MSR methods currently available.

Conflict of Interests:

The authors declare that there is no conflict of interests regarding the publication of this paper.

Ethical approval: This article does not contain any studies with human participants or animals performed by any of the authors.

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