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ARTICLE

A FRAMEWORK FOR AUTOMATIC COLORIZATION OF MEDICAL IMAGING

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ABSTRACT

Background: *Good visual quality along with the chromatic information in medical modality significantly improves analysis and diagnosis. This paper presents a novel approach for colorization of medical images preceded by enhancement phase. The heart of proposed framework lies in an efficient enhancement phase, essentially needed for any medical image colorization algorithm.* ***Methods:*** *In this proposed framework, the chromatic value is calculated from target reference images on the basis of intensity and then it is assigned to desired source image to achieve the colorization.* ***Results:*** *The performance of proposed framework is evaluated on various open source medical images datasets, producing benchmark results. Moreover, quality assurance of resulting colorized images is also carried out by computing chromatic information, measurement of enhancement, structural similarity and signal to noise ratio. On close examination, it was observed that resulting images structurally correspond to source input image with significantly enhanced chromatic and visual information justified by quality parameters.* ***Conclusions:*** *The framework can colorize any kind of medical modality which makes it a unique system as compared to other reported algorithms in medical imaging domain. Visual representation statistics and lower time complexity validated its supremacy with other reported methods.*

KEY WORDS
Image processing, medical Images colorization, bioinformatics, enhancement, chromatic information

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INTRODUCTION

The most vital characteristic of materials are colors that contribute in medical image processing for better understanding of biomedical substances. Colorization enhanced the perceptual visibility of grey scale images and videos [1]. Color calibration is one of the essential preprocessing techniques used in computer vision applications. One of the colorization utility known as Black Magic supports users to colorize normal daily life images [2]. On the basis of high quality, colorized medical images assist in different diseases perversion and treatment [3]. Certainly, colorization applications are effectively contributing in entertainment and medical industry.

The proposed algorithm is a novel approach for colorization of medical images that boosts up the treasured information hidden in grey scale images. Visual noise affects the appearance of an image and gives snowy, grainy, textured and speckled form resulting in variation in brightness with no specific pattern. Hence, it is one of the major causes of poor quality in medical imaging [4]. Therefore for the purpose of diagnosis, noise reduction is of fundamental importance [5]. The high contrast of medical modularity also affects accurate diagnosis. Ordinary colorization algorithm for natural images fails to colorize high contrast and noisy medical images. The proposed framework suggests that medical images may get pre-processed through proposed enhancement phase before applying any colorization algorithm, therefore salt and pepper as well as Gaussian noise are removed by a pre-processing phase of colorization.

The main contribution of building proposed framework was to remove all types of noise, restore the medical image and then adopt colorization algorithm to obtain a good quality chromatically improved image. The colorization algorithms are mainly divided into three types, namely automatic coloring, semi-automatic coloring and user coloring methodologies [6].

In 2002, Welsh et al. reported a semi-automatic algorithm for colorization of natural images using L α β color space. This algorithm works well only for natural images but the results for medical images were not accurate as one could not differentiate between different types of tissues [7]. Reported studies for colorization of CT images using threshold based pseudo- coloring techniques increases the processing time, memory and maximum power consumption [8, 9]. Brain MRI colorization using voxel classification by matching luminance distance between source and target image is reported [10]. In another technique, modalities with different weights were fused together to produce colorized medical images [11]. Automatic fusion based colorization study contributed in CT and MRI colorization. Reported technique colorized only small infected portion of CT and MRI image [12]. Similarly, Markov random field was used to determine possible chromatic value with prior estimation [13]. Moreover, wavelet packets were utilized to predict pseudo-random code to produce colorized image [14]. Texture information was used to determine the

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possible chrominance value [15]. Further, video colorization technique to colorize key frame used few color seed and propagated chrominance to remaining pixels. Eventually, remaining similar frames were colorized using generated colorized key frame as reference image [16].

MATERIALS AND METHODS

The proposed framework recommends pre-processing as a key step before applying any colorization process on medical images. The colorization algorithms also differ from other reported studies of colorization of medical images i.e., second and third channels were created in the grey scale image and YCbCr space was used, thus proposed colorization method visually enhances an image. Framework reveals a novel algorithm to colorize any kind of medical modality resulting in a good visual representation and lower time complexity. None of other reported studies uses the second and third channels.

Following pre-processing steps were used for enhancement and noise removal of medical imaging. Initially, noise was removed and contrast of image was adjusted. Edges were highlighted to improve visual understanding. A target color medical image was used as reference to map the chromatic information in input grey scale source image. After mapping, colorized medical image was produced. The quality assessment of resulting colorized medical image was determined by computing quality parameters. An architecture overview of the proposed framework is represented in [Fig. 1].

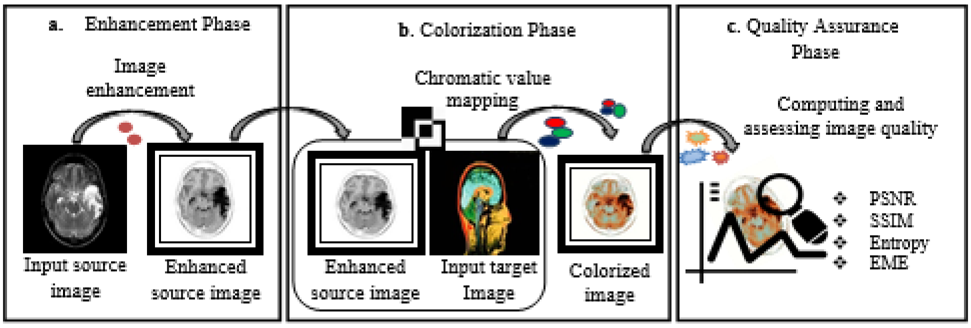

Fig.1: Graphical overview of proposed framework a. enhancing source medical image after preprocessing by enhancement phase b. colorization phase c. quality assurance phase

Image enhancement phase

The grey scale medical images were pre-processed by a series of steps as shown in [Fig. 2]. These enhancement techniques resulted in an improved quality medical image. The source input medical images were acquired of resolution 256×256.

The medical images were converted into process able format and text labels were removed. Noise was removed by weighted averaging filter. Input source image was convolved with weighted kernel of 3×3 pixels neighborhood and resulting pixel under processing with weighted average of its neighboring pixel. Sliding kernel of m×n size was centered at point (x, y) of Image(x, y) where m and n=3.

Considering Zj pixel under processing, whereas, j represents number of pixels ≤9. Rxy denotes an area to compute average of Image(x,y). s and t represent the location of pixel being processed. Following expressions (1-3) represent averaging smoothing process on Image(x, y).

$$\text{Weighted Kernel} = \begin{vmatrix} -1 & -1 & -1 \\ -1 & +12 & -1 \\ -1 & -1 & -1 \end{vmatrix} \quad (1)$$

$$\text{Image}(x,y) = \frac{1}{mn} \sum_{s,t \in R}^{\omega} I(s,t) \quad (2)$$

$$\text{Image}(x,y) = \text{Image}(x,y) * \frac{1}{9} \text{Weighted Kernel} \quad (3)$$

Image(x, y) noise was removed and preceded further for adjusting the contrast to highlight minor details hidden within an image.

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After noise removal, image contrast was enhanced and minor details in an image were accentuated. Intensity distribution equalization was used to normalize intensity of Image(x, y). Transformation function (4) represents intensity distribution equalization value.

$$T = \sum_{i=0}^{r} fp \,.\, \frac{\text{max.intensity img}}{m \times n} \tag{4}$$

Where, fi was the frequency of intensity value p of number of pixels of an image. Intensity equalization is a transformation function of transferring particular pixel intensity with T intensity value at location i.

Edges of medical images were enhanced by using two 3×3 convolution kernels, Kx and Ky producing horizontal and vertical derivatives as shown in expression (5). It dominates the vertical and horizontal edges of Ix, y to enhance the information. In Kx and Ky, kernels were used to enhance the edge information by subtracting pixels above and below the edge. More weights are assigned to pixels across the edges.

$$\mathrm{Kx} = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ +1 & +2 & +1 \end{bmatrix};\ \mathrm{Ky} = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix} \tag{5}$$

Expressions (6-7) represent the edge improvement mathematical formulas.

$$\mathrm{Imgx} = \mathrm{Kx} \ * \ \mathrm{I(x,y)} \tag{6}$$

$$\mathrm{Imgy} = \mathrm{Ky} \ x \ \mathrm{I(x,y)} \tag{7}$$

This makes a noticeable increase in edge intensity and the resulting image became more informative as compared to the original input image. Every pixel value at x, y was being replaced by gradient magnitude at location (x, y) as given in (8).

$$\mathrm{Img(x,y)} = \sqrt{\mathrm{Imgx}^2 + \mathrm{Imgy}^2} \tag{8}$$

The gradient's direction is represented by (9):

$$\angle = \arctan\frac{\mathrm{Imgy}}{\mathrm{Imgx}} \tag{9}$$

The medical image was further processed and its negative was obtained with negative transformation using (10). Negative of image was computed when the dynamic range of image was between [0 to L-1] whereas L is maximum intensity and W is pixel intensity under processing respectively.

$$\mathrm{Neg\ Img(x,y)} = \mathrm{L} - \mathrm{W} \tag{10}$$

The [Algorithm 1] presents sequences of steps for enhancing medical image.

Algorithm1. Enhancement of medical images

Required: Preprocessed image img when r ⟵total number of pixels, where i is pixel under processing
Input: Medical image Image(x,y)
Output: Noise free, sharper edged medical image
Initialization Image(x, y)
Step 1: Resizing Image(x, y) | rows × columns=256
Step 2: Noise removal by weighted averaging filter sliding window of 3×3 convolved with Image(x, y)
while i≠ r do

$$\text{Noise reduced Image}(x,y) \cong \text{Image}(x,y) \text{ convolving Weighted Kernel}$$

end while
Step 3: Contrast improvement by equalizing intensity distribution
while i≠ r do

$$\text{normalized histogram} = \frac{\textit{number of pixels with intensity p}}{\textit{total number of pixels}}$$

end while
Step 4: Edge improvement by computing absolute gradient and direction.
Step 5: Negative of image when dynamic range of image is between [0-L-1], whereas L is maximum intensity and W is x pixels intensity under processing
while i≠ r do

$$\text{Neg Img}(x,y) = \text{maximum intensity} - \text{intensity of pixel under processing}$$

end while

Step 6: Return enhanced medical image

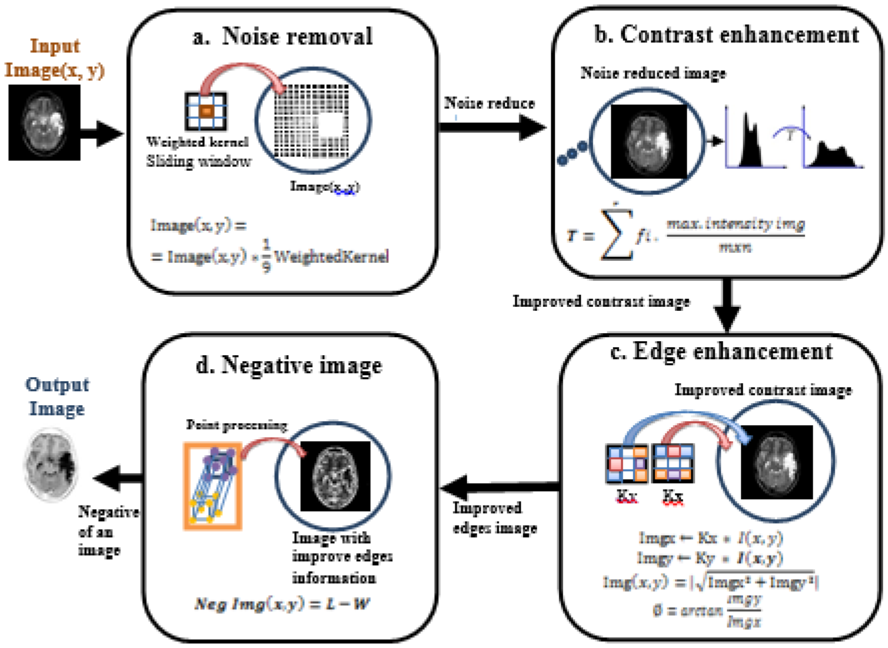

Fig.2: Enhancement phase of proposed methodology a. Noise removal module representing an application of weighted averaging filter on an image b. Contrast enhancement module on an application of transformation function c. Edge enhancement module using Kx, Ky mask convolving with an image and computing gradient with phase d. Negative of an image for better colorization

Colorization Phase

Colorization phase requires input enhanced grey scale source image of 256×256 resolution and target colored medical image of 256×256 resolution to produce a colorized medical image of 256×256 resolution.

The source grey scale medical image has one dimension. In order to convert it into three-dimensional image so that it can hold chromatic information, a second and third channel of size 256×256 was added in it. Initially, a new channel was populated with ones and later these values were updated with the computed chromatic value assigned to the source image. [Fig. 3] depicts the series of steps for colorization of medical images.

Normalization was performed on the input source grey scale image to bring pixels intensity compatible with the target image. In this way, intensity of an image is limited in the specified range. Normalized pixel intensity value N of source image s is shown in (11), where L is maximum intensity value and P is minimum intensity value. The pixel at location x, y was convolved with a maximum value of intensity i.e., 255. The resulting value was divided by 255-(L-P). The intensity of pixel (x,y) was normalized within maximum and minimum intensity range.

$$\text{Normalized pixel value} = \frac{I \times 255}{255 - (L - P)} \tag{11}$$

Then both images i.e., grey scale input source image s and colored target image t was converted into YCbCr color.

Pixels intensity was compared using Y channel of YC_bC_r of two images and all the source input image pixels were mapped with chromatic value using target image chromatic information. After successful chromatic value assignment, the source image was converted into RGB color space for visualization.

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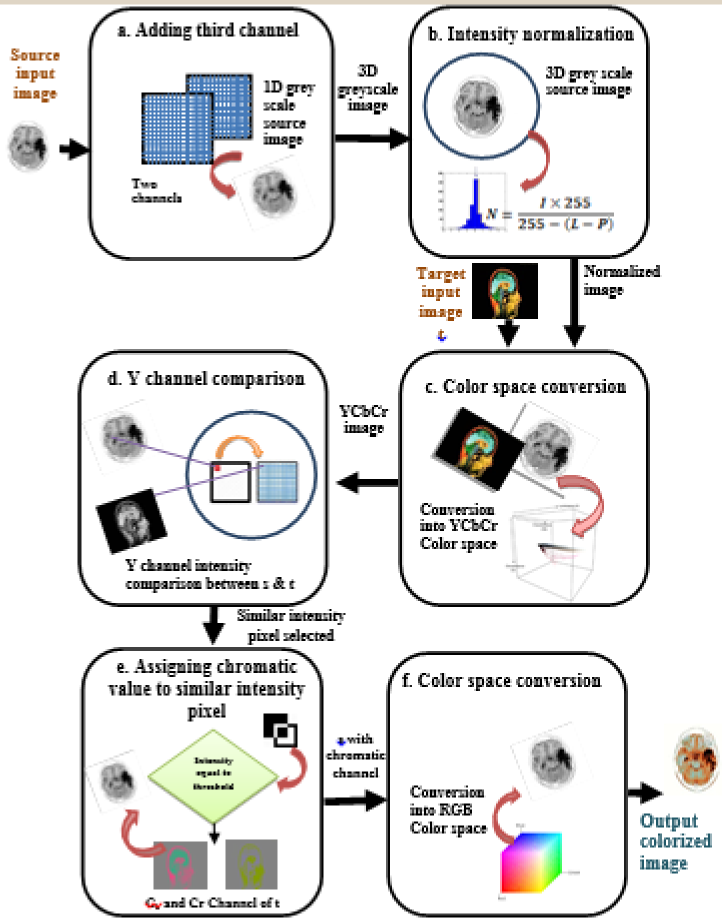

Fig. 3: Colorization phase of proposed methodology **a.** two channels are inserted in 1D grey scale image to form it 3D grey scale image **b.** normalization of grey scale 3D image **c.** converting both target and source image into YC_bC_r **d.** comparing Y channel pixels intensity **e.** similar intensity value pixels chromatic value C_b C_r of t transferred to the source image. **f.** color space conversion from Y YC_bC_r to RGB for displaying.

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The [Algorithm 2] presents sequences of steps for colorizing medical image.

Algorithm2. Colorization of medical images

Required: Colorized image col_img, when r ←total number of pixels of source grey scale medical image s, where i is pixel under processing
Input: Pre-processed source grey scale medical image s and target color medical image t
Output: Colorized medical image
Initialization
Step 1: Adding second and third channels in s
Step 2: Normalized intensity value of s, where L is maximum intensity and P is minimum intensity

$$P \le Normalized\ pixel\ intensity\ \le L\ ,$$

$$0 \le P, L \le 256, normalized\ pixel\ intensity\ \subseteq L$$

Step 3: Converting s and t into YCbCr color space
Step 4: Assigning chromatic value to s
while i≠ r do
Comparing intensity value between s and t
if intensity matched
Transfer the chromatic value from t to s
else
Compare the next pixel
end if
end while
Step 5: Converting s from YCbCr color space to RGB color space
Step 6: Return enhanced colorized medical image col_img

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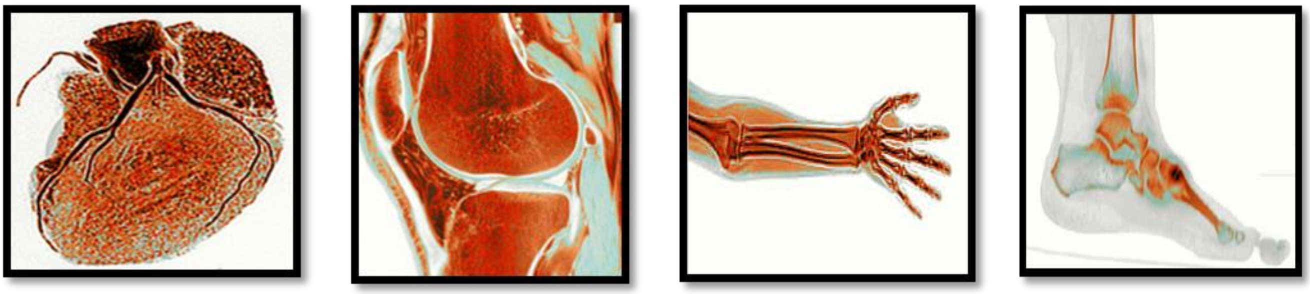
RESULTS

Dataset

The open source dataset's seventy images were utilized for experimental evaluation of proposed framework [18-21].

Results

The proposed algorithm gives a meaningfully better understanding of medical image. On precise observation, various cells, tissues, blood vessels, bones and organs can be significantly examined. Technically it has better efficiency on visual and computation grounds from the reported algorithms [1-16] which show its supremacy as a highly sophisticated medical instrument. The strength of proposed framework is its operational capacity on all types of medical modalities. The average computation time required for colorization was approximately 0.9-1 seconds. The resulting colorized outputs of medical modality validate substantially good visual representation of medical images generated by the proposed algorithm as displayed in [Fig. 4].



a. b. c. d.

Fig. 4: (a-d): Colorized output of MRI, CT, X-ray and PET images generated by the proposed framework

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As all minor details are not fully represented by grey scale medical images, therefore sometimes healthy tissues of similar pixels intensity are considered as infectious by medical experts due to the high contrast of medical modality. Resulting colorized images displayed above justified vivid enhancement methodology rationally contributing in anomalies detection, including cancerous tissues and internal bleeding. Medical images substantially colorized at run time with an average colorization time of 0.6 milliseconds. Colorization utility using proposed algorithm colorized medical images installed at clinical instruments for inspecting human anatomy. Potentially, it supports in real time scenario that leads to faster diagnosis and overall improved patient care as well as increasing the survival rate.

PERFORMANCE EVALUATION

To justify the enhancement in color and information performance, parameters were computed to assure image quality [22-24]. Various statistical performance metrics were calculated to assert the enhanced quality of proposed algorithm resulting colorized images shown in [Table 1]. Quality assurance parameters under considerations are peak signal to noise ratio (PSNR), measure of enhancement (EME), structural similarity index (SSIM) and entropy.

Table 1: Quality parameters of resulting colorized medical images

Medical Modality	PSNR	SSIM	Entropy		EME	
			Input Image	Output Image	Input image	Output Image
CT	80	0.8	0.05	1	10	20
MRI	78	0.9	0.02	3	1	19
Mammogram	70	1	0.04	2	5	39
Nuclear Medicine	65	0.8	0.2	15	1	19
PET	60	0.9	0.1	2	4	15
Ultrasound	70	1	0.01	1	6	19
X-ray	80	1	0.2	2	2	9

The good quality images PSNR value is higher than 20dB [22]. The PSNR value was calculated between resultant colorized medical imaging and input grey scale medical imaging. All the resultant images PSNR values are greater than 50, thus good quality images generated by proposed framework. Ultrasound, X-ray, and PET samples PSNR values strike 99 dB value, depicting zero MSE (mean square error) between input and colorized image.

SSIM was computed to examine luminance, structure and contrast similarity between colorized image c and source image s. Greater the value of entropy, greater the information content present in an image

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[23]. The obtained range of SSIM value was between 0.8- 1. Mammogram, ultrasound and X-ray images mean SSIM value is 1 which was highest among all the other types of images. CT images mean value was smaller as compared to other mean values. Overall the proposed colorization algorithm did not degrade the structural contents, contrast or luminance information. Best resulting SSIM values were obtained from Ultrasound and X-ray. The entropy of colorized image was much improved and justified information within the colorized image was enhanced. PET and Nuclear medicine colorized images hold the maximum mean value of entropy. Colorization framework increases the entropy value of subject image.

A higher value of the measure of enhancement EME denotes a higher contrast and information clarity in an image. There should be an optimal value of EME to preserve contrast and local features to enhance image details [24]. Resulting EME value was within an optimal range and cause of good visual quality images.

Comprehensive comparison with state of arts studies

The quantitative comparison of proposed methodology with following state of art colorization algorithms, such as Welsh, et. al. color transfer colorization using Lαβ color space [7], Noda, H., et. al. algorithm [13], Kyung woo., et. al. [14], Lipowezky., et. al. algorithm [15] and Horiuchi, T., et. al. algorithm [16] is shown in [Table 2].

Table 2: Quality comparison of resulting colorized medical images with state of art methodologies

PSNR comparison with reported studies						
Methodology	Image 1	Image 2	Image 3	Image 4	Image 5	Image 6
Proposed algorithm	52	65	71	61	73	99
Noda, H. et. al. algorithm [13]	30	15	27	19	17	26
Welsh et. al. algorithm [7]	21	35	30	29	31	27
kyung woo et. al. algorithm [14]	21	20	20	19	21	18
Lipowezky et. al. algorithm [15]	25	35	31	19	30	25
Horiuchi, T., et. al. algorithm [16]	30	25	29	32	27	30

The parameters of all algorithms were kept optimally same to achieve highest computable PSNR. The proposed algorithm PSNR curve is quite higher than the existing state of art algorithms. The proposed enhancement phase before applying colorization algorithm is significantly one of the factors for highest quality of resulting colorized medical images.

CONCLUSION

The main objective of this medical image enhancement research is to facilitate medical professionals in identification of various biological structures. Hence, possibly medical colorized images supports in accurate and prompt analysis of patients disease along with suitable medication. Quality assurance parameters were computed to support and estimate the improvement in chromatic value, brightness, contrast and perceptual appearance. One of the greatest contributions of proposed methodology was that structural features remained same on the addition of chromatic features. Future research can focus on constructing clinical decision support system using colorized medical imaging for robust diagnosis and precise medical treatment.

CONFLICT OF INTEREST
The authors declare no conflict of interest

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FINANCIAL DISCLOSURE
None

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